



Optimizing integrated passenger-freight transport in demand-responsive services: System efficiency and policy insights

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ARTICLE INFO

Keywords:

Integrated passenger freight transport
Demand responsive transport
Vehicle routing problem
System efficiency

ABSTRACT

This paper examines an Integrated Passenger-Freight Transport (IPFT) approach for Demand-Responsive Transport (DRT) services that serve parcel deliveries alongside passenger trip requests in low-demand or rural mobility contexts while preserving passenger service reliability. The problem distinguishes passenger and freight services through their flow structures, capacity dimensions, service-time components, time-window treatments, and cost representations. It is formulated as a Mixed-Integer Linear Programming (MILP) model that minimizes total system costs, including vehicle and driver operating costs, passenger travel time costs, freight time-window penalties, and emission costs. To solve realistic-size instances, we develop a new hybrid solution algorithm, PSA-GA, combining Population-based Simulated Annealing (PSA) with parent selection and crossover mechanisms from a Genetic Algorithm (GA). Planning and policy implications are assessed through a real-world case study in Kirchheim bei München, Germany, supported by extensive sensitivity analyses on cost structures, demand levels and heterogeneity, temporal demand alignment, travel time uncertainty, and vehicle utilization. Results show that IPFT can reduce total costs by 24 % compared with conventional segregated passenger-freight transport (SPFT) systems. Cost savings increase when freight demand is shifted toward lower-passenger-demand periods, whereas overlapping passenger and freight peaks reduce the benefits of integration. IPFT performance is more strongly linked to overall vehicle utilization than to passenger occupancy alone; although passenger occupancy is slightly lower in the IPFT fleet than in the SPFT passenger-only fleet, the integrated system achieves higher combined utilization through joint passenger-freight routing. Fleet size results further indicate that passenger time value and vehicle operating costs are the most influential planning parameters.

1. Introduction

Cities and transportation systems worldwide are increasingly challenged to address a range of interconnected issues, including reducing greenhouse gas emissions, alleviating urban congestion, optimizing existing infrastructure utilization, and ensuring equitable access to mobility services in both urban and rural contexts. Conventional approaches, which typically separate passenger and freight transport, can often exacerbate these issues by duplicating vehicle trips, underutilizing available resources, and increasing environmental externalities. In response, Integrated Passenger-Freight Transport (IPFT) has emerged in recent years as a promising paradigm

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for streamlining transportation systems by combining passenger and freight movement within shared fleets and infrastructure (Antoniou et al., 2023).

Initially introduced by the European Commission (EC, 2007) and further explored through concepts such as “Cargo Hitching” (Van Duin et al., 2019) and “Integrated Passenger-Freight Logistics” (Bruzzzone et al., 2021), IPFT seeks to enhance infrastructure utilization, reduce emissions, and improve service quality by integrating passenger and freight operations. This approach holds significant policy relevance, offering the dual benefits of operational cost savings and improved sustainability in urban mobility.

By integrating passenger and freight demand, IPFT has the potential to reduce vehicle kilometers traveled, lower operational costs, and mitigate environmental impacts, benefits evidenced by pilot projects such as the Dinalog Cargo Hitching¹ initiative. These initiatives showcase how shared infrastructure, vehicles, and public spaces can enhance system-wide efficiency while maintaining service quality, highlighting the potential of IPFT as a policy approach for addressing urbanization, climate change, and rural accessibility challenges (Zhu et al., 2023).

The real-world relevance of IPFT is evident in various applications, from shared railway corridors in the United States (Talebian and Zou, 2015) and the Netherlands (Ursavas and Zhu, 2018) to ferry-based systems in Sweden (Ringsberg, 2023), incentive-driven rural bus services in China (He and Guan, 2023), and transit planning innovations in Brazil (Oliveira et al., 2024). Comparative studies between Europe and Australia further accentuate its feasibility across different contexts (Kiba-Janiak et al., 2021). In urban settings, researchers such as He et al. (2022), Qu et al. (2022), and Cheng et al. (2023a) highlight IPFT’s potential to reduce congestion and emissions.

Despite growing research interest in IPFT, the integration of freight delivery into public transport has primarily concentrated on fixed-route systems, such as metro and rail systems. In contrast, less attention has been given to this integration into demand-responsive transport (DRT) services, which operate with flexible routes and schedules. This issue is particularly noteworthy given the high adaptability of DRT services to accommodate diverse individual mobility needs, especially in low-demand or rural areas.

Incorporating parcel delivery into DRT services can offer strategic opportunities for operators, particularly in rural or low-demand areas. By partnering with logistics providers or public agencies, DRT operators can extend their role beyond passenger mobility to include last-mile delivery. This integration can enhance fleet utilization, create new revenue streams (especially during off-peak passenger hours), and offer a cost-effective alternative in areas where standalone parcel delivery is economically unviable. Moreover, it improves service accessibility and reinforces the role of DRT as a public service.

In this context, our study explores the IPFT concept within the context of DRT services to derive policy-relevant insights into key dimensions of this integrated mobility approach, including economic efficiency, service reliability (considering the differing time sensitivities and scheduling priorities of passenger and freight transport to ensure appropriate prioritization of passenger satisfaction and compliance with public transport regulations), environmental sustainability, and operational feasibility. Overall, this study makes three main contributions:

- 1) We investigate the IPFT approach in the context of DRT services by introducing a problem that addresses the practical routing and scheduling of DRT vehicles to accommodate both passenger and freight demand in a network, as illustrated in Fig. 1. This problem, called the Demand-Responsive Integrated Passenger-Freight Vehicle Routing Problem (DR-IPFVRP), is formulated as a Mixed-Integer Linear Programming (MILP) model that minimizes total system costs, including vehicle and driver operating costs, passenger travel time costs, penalties for freight delivery time window violations, and emissions (CO₂ and primary air pollutants). This comprehensive cost structure enables a systematic evaluation of key policy and operational trade-offs (such as service quality, efficiency, and environmental performance), which are critical to the design of integrated transport systems.
- 2) To efficiently solve the DR-IPFVRP, we develop a new hybrid solution algorithm, PSA-GA, which combines Population-based Simulated Annealing (PSA) with parent selection and crossover operators from a Genetic Algorithm (GA).
- 3) We thoroughly examine the planning and policy implications of implementing IPFT through DRT services, based on a real-world case study in Kirchheim bei München, Germany. This assessment is complemented by extensive sensitivity analyses on key factors, including cost parameters, demand levels and heterogeneity, temporal demand alignment, travel time uncertainty, and vehicle utilization.

The remainder of this paper is organized as follows. Section 2 reviews the literature relevant to this study. Section 3 presents the model formulation of the proposed DR-IPFVRP. Section 4 describes the solution algorithms and evaluates their performance through computational experiments. Section 5 discusses planning perspectives and policy implications based on a real-world case study and extensive sensitivity analyses. Finally, Section 6 concludes the paper by summarizing the key findings and offering recommendations for future research.

2. Literature review

This section reviews two key research streams that frame our study, including VRP and IPFT literature. The first part focuses on VRP models related to our work and the solution algorithms widely used to solve them. The second part examines the IPFT literature, highlighting how this integrated transport approach can support broader policy goals, such as sustainability, equity, and operational

¹ <https://www.utwente.nl/en/bms/iems/research/researchprojects/project-archive/dinalogcargohitching/>.

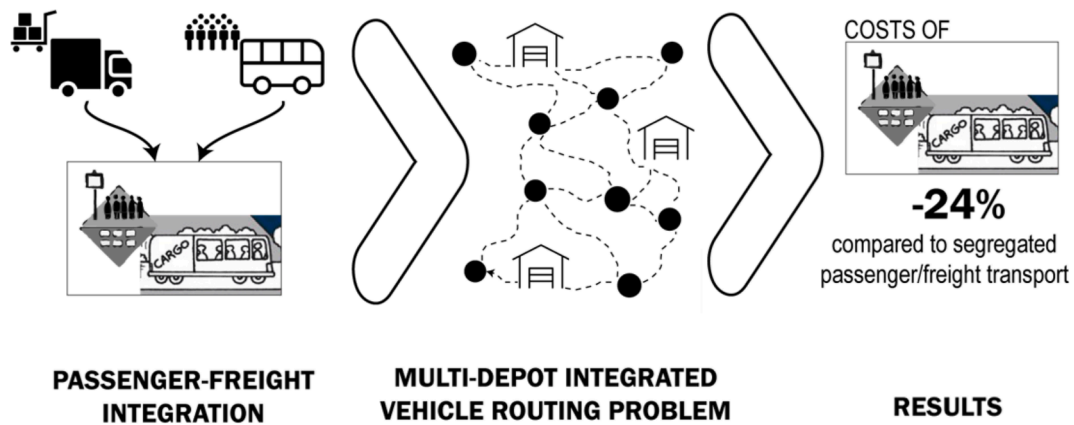


Fig. 1. Schematic representation of the proposed demand-responsive integrated passenger-freight transport problem.

efficiency.

2.1. Vehicle routing problem

The VRP is a well-studied problem in transportation and logistics, focused on determining efficient routes and schedules for a fleet of vehicles to serve a set of customer nodes (demand points) while minimizing total travel costs (Toth and Vigo, 2014). The VRP has been expanded into several variants to better represent the real-world aspects of transportation systems, such as the Green VRP (GVRP) and the Multi-Depot VRP (MDVRP). These variants incorporate environmental performance metrics and multiple depot structures, respectively, aligning with broader goals of emissions reduction and operational efficiency.

In the context of the GVRP, researchers have integrated emission factors into routing models to support environmentally sustainable decision-making. These models consider real-world factors such as traffic congestion, driving speeds, road gradients, and vehicle characteristics. Common emission estimation frameworks include the Comprehensive Modal Emission Model (CMEM) (Barth et al., 2005; Koç et al., 2014), the Methodology for Calculating Transport Emissions and Energy Consumption (MEET) (Çimen and Soysal, 2017), and the Computer Programme to calculate Emissions from Road Transportation (COPERT²) (Molina et al., 2019; Jin et al., 2022; Ge et al., 2023; Ge and Jin, 2023). Among these, the COPERT model, developed by the European Environment Agency, estimates not only CO₂ emissions but also four key pollutants, namely carbon monoxide (CO), nitrogen oxides (NO_x), volatile organic compounds (VOCs), and particulate matter (PM), thereby offering a practical tool for broadly assessing the environmental impact of routing decisions within a policy-oriented framework.

The MDVRP has also been examined to address vehicle assignment and routing from multiple geographically distributed depots, intending to enhance fleet utilization when serving spatially dispersed demand across a network (Jabir et al., 2017; Li et al., 2019; Peng et al., 2020; Sadati and Çatay, 2021).

Due to the NP-hard nature of VRPs, heuristic algorithms have been the most widely used approaches to solve large instances of these problems within reasonable computational (CPU) times (for an in-depth review, see Elshaer and Awad, 2020; Garside et al., 2024). Common approaches include Tabu Search (TS) (Cordeau and Maischberger, 2012), Simulated Annealing (SA) (Vincent et al., 2022), Genetic Algorithms (GA) (Mohammed et al., 2017), Grey Wolf Optimizer (GWO) (Liu et al., 2022), Ant Colony Optimization (ACO) (Tirkolaee et al., 2019), and Particle Swarm Optimization (PSO) (Lo, 2022). In recent years, hybrid metaheuristics have gained increasing attention for their ability to integrate the strengths of different algorithms and enhance search performance. For instance, Sadati and Çatay (2021) combined Variable Neighborhood Search (VNS) with TS for solving the MDGVRP, while Aghadavoudi Jolfaei and Alinaghian (2024) combined evolutionary local search with Large Neighborhood Search (LNS) for solving the MDVRP.

2.2. Integrated passenger-freight transport

IPFT combines the transportation of passenger and freight flows to optimize resource utilization, a concept with significant policy potential to reduce congestion, emissions, and transport costs while improving access to services (Antoniou et al., 2023). IPFT has been explored in various contexts, including mass rapid transit networks (Hu et al., 2022), metro systems (Zuo et al., 2023), last-mile delivery services (Bruzzone et al., 2021), modular vehicle operations (Hatzenbühler et al., 2023, 2024), and innovative modes such as drone-assisted delivery (Cheng et al., 2023b). These applications suggest that IPFT can support policies promoting sustainable logistics and equitable access.

In the operations research field, IPFT has predominantly been studied in railway and fixed-route public transport systems, focusing on capacity allocation and scheduling optimization (e.g., Liu and Dessouky, 2017; Behiri et al., 2018; Li et al., 2021; Sahli et al., 2022;

² Full details can be found at <https://www.emisia.com/utilities/copert/>.

Xu et al., 2022). These studies often use heuristic and metaheuristic solution methods, such as ACO (Behiri et al., 2023) and GA (Sahli et al., 2022). Moreover, IPFT applications in passenger bus networks have highlighted the potential of public transport systems to support last-mile logistics while reducing duplicated vehicle movements (Machado et al., 2023).

Although IPFT offers clear potential benefits, the literature also highlights several operational, behavioral, and governance-related challenges that must be considered when designing integrated services. From an operational perspective, combining passenger and freight flows introduces non-trivial trade-offs between vehicle utilization, routing flexibility, service reliability, and delivery punctuality. In particular, the additional detours or dwell times required for freight handling may improve fleet productivity and reduce vehicle-kilometers traveled, but they can also increase passenger travel times, reduce schedule reliability, and complicate capacity management inside vehicles. These trade-offs are especially relevant in DRT systems, where route and schedule flexibility must be balanced with waiting time, detour time, and the need to maintain an acceptable level of service for passengers. Previous studies on DRT have shown that flexibility can improve coverage and system efficiency, but only if spatial and temporal service constraints are carefully designed; otherwise, excessive flexibility may reduce operational viability or passenger attractiveness (Alonso-González et al., 2018; Sørensen et al., 2021). In IPFT contexts, this implies that passenger service quality should not be treated as equivalent to freight delivery performance, since passengers are generally more sensitive to in-vehicle time, waiting time, and arrival-time reliability.

Behavioral and user-acceptance factors are also central to IPFT implementation. Cavallaro et al. (2023), using a Delphi survey with international stakeholders, showed that IPFT design should account for service attributes such as information provision, environmental performance, passenger-freight space division, safety, security, and potential fare reductions to compensate passengers for changes compared with conventional passenger-only services. More recently, Mazzulla et al. (2026) explicitly examined IPFT from the perspective of public transport users through a stated preference experiment and a random parameter logit model. Their results showed that in-vehicle travel time is the most influential attribute shaping passengers' preferences, while fare, service frequency, and available passenger space also affect user acceptance. Therefore, IPFT should not be evaluated only through operational cost savings or routing efficiency, but also through its perceived acceptability and service-quality impacts on passengers.

IPFT also raises important regulatory, economic, and social policy issues. Regulatory barriers, such as vehicle design restrictions³, safety standards, liability issues, and rules governing the co-presence of passengers and goods, can hinder implementation (Mazzulla et al., 2026). At the same time, policy instruments such as tax incentives, green fleet subsidies, public-private partnerships, or dedicated support for rural mobility and logistics services can accelerate adoption. Urban policies might prioritize IPFT to alleviate congestion through shared-use infrastructure, as seen in pilot applications and freight-on-transit concepts, while rural policies could leverage IPFT to consolidate sparse passenger and freight demand and improve access to essential services (Bruzzone et al., 2023a). From a socioeconomic perspective, IPFT can enhance access to both mobility and goods, aligning with equity-oriented transport policies, particularly in areas where conventional passenger and freight services are economically difficult to sustain.

In addition, successful IPFT implementation requires suitable governance and institutional arrangements. Unlike conventional passenger-only or freight-only systems, integrated services encompass multiple actors, including public transport authorities, logistics providers, municipalities, vehicle suppliers, technology providers, and users. This multi-actor structure creates challenges related to data sharing, cost and revenue allocation, service responsibilities, liability, and coordination between passenger-oriented and freight-oriented objectives. Similarly, review studies highlight the need to better incorporate stakeholder preferences, governance mechanisms, and multi-objective performance evaluation into IPFT planning (Cheng et al., 2023a; Derse and van Woensel, 2024).

2.3. Overview of research gaps and study contributions

To summarize, the reviewed literature indicates that most studies on integrating passenger and freight transport within public transport systems have focused on fixed-route services, such as metro and rail systems. However, less attention has been paid to integrating freight delivery into DRT services, which are characterized by flexible routing and scheduling that allow them to adapt to diverse and variable mobility needs. This integration potential is particularly significant in low-demand contexts, such as rural areas, where DRT often plays a crucial public service role in addressing a wide range of mobility demands (Antoniou et al., 2023).

Turning to flexible routing, Hatzenbühler et al. (2023) explored simultaneous passenger and freight transport from a VRP-based perspective, using variable-length vehicle platoons, with configurations fixed at a single depot before departure. They employed an Adaptive Large Neighborhood Search (ALNS) algorithm to optimize routes. Hatzenbühler et al. (2024) advanced this concept with a multi-purpose pickup and delivery problem, enabling vehicles to swap passenger and freight modules at depots during trips, again solved using the ALNS algorithm. Applied to Stockholm scenarios, this approach yielded a 13% cost reduction and 33% shorter trip durations.

Nonetheless, both studies leave several aspects open for further research in the context of demand-responsive IPFT. First, although these integrated systems account for two distinct demand types (passengers and freight), the critical difference in their time sensitivities (i.e., service priorities) is not addressed. In this integrated setting, ensuring service reliability for passengers requires a higher scheduling priority, as public transport passengers typically expect strict adherence to scheduled arrival times, whereas freight deliveries generally allow greater temporal flexibility. Neglecting this distinction can lead to an underestimation of the operational constraints required for equitable and passenger-centered planning. Furthermore, it may undermine passenger satisfaction and conflict

³ Appendix A presents vehicle design solutions, such as modifications for minibuses and vans to balance passenger comfort with freight efficiency, offering critical insights for policy implementation.

with regulatory requirements in public transport contexts.

Second, environmental impacts (e.g., CO₂ and primary air pollutants) and operational uncertainties (e.g., uncertain travel times) are not incorporated into their modeling frameworks. Third, they are limited to a single-depot setting and do not account for a multi-depot structure, where optimizing vehicle assignments across multiple depots in the network is crucial for improving fleet utilization and operational efficiency. Fourth, both studies rely solely on the ALNS algorithm, without exploring alternative or hybrid meta-heuristic approaches that could offer improved performance for this NP-hard problem.

Our study addresses these limitations by introducing the DR-IPFVRP, which operationalizes the IPFT approach in the context of DRT services and provides key policy insights into this integrated mobility approach. The proposed model, formulated as a MILP model, offers a practical planning framework for optimizing the routing and scheduling of shared DRT vehicles to serve both passenger and freight demand points within a network. The objective is to minimize a comprehensive system cost function, encompassing vehicle and driver operating costs, passenger travel time costs, penalty costs for freight time window violations, and emission costs (CO₂ and primary air pollutants estimated using the COPERT model). The model also incorporates travel time uncertainty to assess its influence on planning and operational outcomes.

The model captures the differing time sensitivities and priority requirements of passenger and freight transport. Specifically, hard (inviolable) time windows are imposed for passengers to ensure service reliability and compliance with regulatory standards in public transport settings. In contrast, soft time windows are applied to freight deliveries, allowing controlled flexibility through penalized deviations. This differentiation reflects real-world operational priorities, where passenger reliability is critical, and supports the development of more equitable and passenger-centric mobility systems.

To efficiently solve this complex problem, we develop a hybrid solution algorithm, PSA-GA, combining the strengths of PSA and GA. The algorithm is validated against optimal solutions obtained from the Gurobi solver on small- and medium-scale instances and demonstrates superior performance compared to conventional heuristics (GA, PSO, and GWO) on larger-scale problems.

Finally, we conduct a comprehensive investigation into the planning and policy implications of deploying DRT services under the IPFT framework through a real-world case study in Kirchheim bei München, Germany. This analysis is supported by extensive sensitivity experiments covering key planning variables, including cost structures, demand levels and heterogeneity, and travel time uncertainty. Our findings demonstrate that IPFT can generate economic and environmental benefits while offering policy-relevant insights into fleet sizing, vehicle utilization, demand management, and service reliability in flexible DRT systems. The proposed modeling and solution framework can therefore serve as a decision-support tool for public transport agencies and operators to evaluate IPFT strategies under different demand patterns, cost conditions, and operational settings in both urban and rural contexts.

3. Problem description and formulation

This section presents the DR-IPFVRP. Subsection 3.1 defines the problem, outlining its scope, objectives, and key characteristics. Subsection 3.2 presents the mathematical formulation of the model.

3.1. Problem description

The DR-IPFVRP models and optimizes the routing and scheduling of a fleet of DRT vehicles to concurrently transport passengers and deliver parcels. The problem determines efficient routes and schedules that serve both passenger and freight demands while minimizing total system costs.

Passenger transport in the model supports flexible trip patterns, encompassing both depot-to-node trips (where passengers board at depots and alight at customer nodes) and node-to-node trips (where passengers board and alight between customer nodes). To model this, we introduce explicit boarding and alighting parameters (e.g., b_i for passengers boarding at node i and d_i for those alighting) along with passenger flow variables tracking the number of passengers carried by each vehicle on each arc. In contrast, freight transport follows a depot-to-node structure, where parcels are collected at depots and delivered to designated customer nodes.

Hard time windows are imposed on passenger transport to ensure service quality in this integrated system, requiring strict adherence to specified arrival constraints. In contrast, freight deliveries operate under soft time windows, where deviations from the designated interval $[bt_i^f, et_i^f]$ are allowed but result in penalty costs in the objective function. Routing and scheduling decisions are optimized to ensure that each customer node is visited exactly once, while simultaneously satisfying passenger- and freight-related constraints. Furthermore, the assignment of vehicles to depots is optimized to enhance fleet utilization and overall operational efficiency.

It is important to distinguish the proposed passenger-freight integration from a formulation that only addresses two user groups with different time windows or cost parameters. The DR-IPFVRP is built on a passenger-oriented DRT system, into which parcel delivery operations are integrated as a complementary service. Passenger mobility remains the primary public transport function, while parcel delivery uses available vehicle capacity subject to passenger-priority service constraints and associated routing trade-offs. Accordingly, passenger and freight demands differ not only in temporal flexibility but also in operational structure, flow conservation logic, service priorities, capacity use, and cost representation. Passenger demand represents mobility requests, including pickup and drop-off requests, and is modeled through passenger flow variables, passenger capacity constraints, hard time windows, and passenger travel time costs. Freight demand, by contrast, represents parcel delivery requests originating from depots and delivered to customer nodes, and is modeled through separate freight flow variables, freight capacity constraints, unloading service times, soft delivery time windows, and earliness/tardiness penalties. Therefore, passengers and freight compete for shared vehicle resources but

impose different service requirements on the system. Table 1 summarizes the main modeling distinctions between passenger and freight services in the proposed DR-IPFVRP.

3.2. Problem formulation

Table 2 defines the notation used in our model. Eq. (1) presents the objective function to minimize total costs. The first term accounts for emission⁴ costs incurred across all traversed arcs. The second term represents vehicle operating costs based on the operating time of each active vehicle. The third term captures human driving costs. The fourth term calculates passenger trip time costs by multiplying the number of passengers traveling on each arc by the corresponding travel time. The fifth and sixth terms impose penalty costs for early and late parcel deliveries at customer nodes, respectively.

$$\begin{aligned}
 \text{Min } Z = & \lambda_1 \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} e_{ij} x_{ijk} \\
 & + \lambda_2 \sum_{k \in K} y_k (a_k^{\text{ret}} - a_k^{\text{dep}}) \\
 & + \lambda_3 \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ijk} \\
 & + \lambda_4 \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} u_{ijk} (a_{jk} - a_{ik}) \\
 & + \lambda_5 \sum_{k \in K} \sum_{i \in C} \max\{0, b_i^{\text{t}} - a_{ik}\} + \lambda_6 \sum_{k \in K} \sum_{i \in C} \max\{0, a_{ik} - e_i^{\text{t}}\}
 \end{aligned} \tag{1}$$

Subject to:

$$\sum_{d \in D} r_{dk} = y_k, \quad \forall k \in K \tag{2}$$

$$\sum_{j \in N} x_{djk} = r_{dk}, \quad \forall d \in D, k \in K \tag{3}$$

$$\sum_{i \in N} x_{idk} = r_{dk}, \quad \forall d \in D, k \in K \tag{4}$$

$$\sum_{k \in K} \sum_{j \in N} x_{ijk} = 1, \quad \forall i \in C \tag{5}$$

$$\sum_{j \in N} x_{ijk} - \sum_{j \in N} x_{jik} = 0, \quad \forall i \in C, k \in K \tag{6}$$

$$\sum_{j \in N} u_{ijk} - \sum_{j \in N} u_{jik} = (b_i - d_i) \sum_{j \in N} x_{ijk}, \quad \forall i \in C, k \in K \tag{7}$$

$$\sum_{j \in N} s_{ijk} - \sum_{j \in N} s_{jik} = f_i \sum_{j \in N} x_{ijk}, \quad \forall i \in C, k \in K \tag{8}$$

$$u_{ijk} \leq P x_{ijk}, \quad \forall i, j \in N, k \in K \tag{9}$$

$$s_{ijk} \leq F x_{ijk}, \quad \forall i, j \in N, k \in K \tag{10}$$

$$c_{ij} \sim \text{Lognormal}(o_{ij}, \sigma_{ij}), \quad \forall i, j \in N \tag{11}$$

$$g_i = \alpha_p(b_i + d_i) + \alpha_f f_i, \quad \forall i \in C \tag{12}$$

$$a_{jk} \geq a_{ik} + g_i + c_{ij} x_{ijk} - M(1 - x_{ijk}), \quad \forall i, j \in N, k \in K \tag{13}$$

$$a_k^{\text{dep}} + c_{dj} \leq a_{jk} + M(1 - x_{djk}), \quad \forall d \in D, j \in N, k \in K \tag{14}$$

$$a_{ik} + c_{id} \leq a_k^{\text{ret}} + M(1 - x_{idk}), \quad \forall i \in N, d \in D, k \in K \tag{15}$$

$$b_i^{\text{t}} \leq a_{ik} \leq e_i^{\text{t}}, \quad \forall i \in C, k \in K \tag{16}$$

⁴ We use the COPERT-derived equation $e_{ij} = \alpha_1 v_{ij} + \alpha_2 v_{ij}^2 + \alpha_3 v_{ij}^3 + \alpha_4 d_{ij} v_{ij} + \alpha_5 d_{ij}$ to estimate the amount of pollutants (grams) produced by a vehicle traveling on arc (i, j) , where $v_{ij} = d_{ij}/o_{ij}$ is the average driving speed on arc (i, j) , obtained by dividing the arc distance d_{ij} by the mean travel time o_{ij} , and $\alpha_1, \alpha_2, \alpha_3, \alpha_4$, and α_5 are coefficients specific to the vehicle and pollutant type (Emisia SA, 2024).

Table 1
Modeling distinctions between passenger and freight services in the DR-IPFVRP.

Dimension	Passenger service	Freight service
System role	Primary DRT/public transport function	Complementary parcel delivery activity
Demand structure	Mobility (pickup and drop-off) demand	Parcel delivery demand
Service movement structure	Depot-to-node and node-to-node passenger trips	Depot-to-node parcel deliveries
Flow variable	Passenger flow u_{ijk} with boarding and alighting	Freight flow s_{ijk} with delivery-based conservation
Capacity dimension	Passenger capacity P	Freight capacity F
Time-window treatment	Hard (inviolable) time windows	Soft time windows
Cost representation	Passenger trip time costs	Delivery time-window violation (earliness and tardiness) penalties
Service-time component	Passenger boarding and alighting times at customer nodes	Parcel unloading time at customer nodes
Policy priority	Reliability and service quality for public transport users	Flexible use of available capacity for parcel delivery

Table 2
Notation list.

Symbol	Description
Sets and indices	
D	Set of depots
C	Set of customer nodes
N	Set of all nodes, $N = D \cup C$
K	Set of vehicles
i, j	Node index
k	Vehicle index
d	Depot index
Parameters	
d_{ij}	Distance on arc (i, j) (km)
c_{ij}	Actual travel time on arc (i, j) (h)
σ_{ij}	Mean travel time on arc (i, j) (h)
σ_{ij}	Standard deviation of travel time on arc (i, j) (h)
g_i	Service time at node i (h)
e_{ij}	Amount of pollutants produced on arc (i, j) (g)
b_i	Number of passengers boarding at node i
d_i	Number of passengers alighting at node i
f_i	Freight demand delivered to node i
P	Vehicle capacity for passengers
F	Vehicle capacity for freight
A	Maximum fleet size
α_p	Time required per passenger for boarding/alighting (h)
α_f	Time required per unit of freight for loading/unloading (h)
$[bt_i^p, et_i^p]$	Passenger time window at node i (h)
$[bt_i^f, et_i^f]$	Freight time window at node i (h)
$[t_s, t_r]$	Depot operating time window (h)
λ_1	Cost of unit air pollutants (£/g)
λ_2	Vehicle operating cost (£/h)
λ_3	Human driving cost (£/h)
λ_4	Passenger trip time cost (£/h)
λ_5	Penalty cost for early delivery (£/h)
λ_6	Penalty cost for late delivery (£/h)
M	A large constant
Decision variables	
x_{ijk}	Binary variable, equals 1 if vehicle k traverses arc (i, j) , otherwise 0
y_k	Binary variable, equals 1 if vehicle k is used, otherwise 0
r_{dk}	Binary variable, equals 1 if vehicle k is assigned to depot d , otherwise 0
a_{ik}	Arrival time of vehicle k at node i
a_k^{dep}	Departure time of vehicle k from its assigned depot
a_k^{ret}	Return time of vehicle k to its assigned depot
u_{ijk}	Passenger flow transported by vehicle k on arc (i, j)
s_{ijk}	Freight flow transported by vehicle k on arc (i, j)

$$\sum_{k \in K} y_k \leq A \quad (17)$$

$$x_{ijk} \in \{0, 1\}, \forall i, j \in N, k \in K \quad (18)$$

$$y_k \in \{0, 1\}, \forall k \in K \quad (19)$$

$$r_{dk} \in \{0, 1\}, \forall d \in D, k \in K \quad (20)$$

$$a_{ik} \geq 0, \forall i \in N, k \in K \quad (21)$$

$$a_k^{dep} \geq t_s, \forall k \in K \quad (22)$$

$$a_k^{ret} \leq t_r, \forall k \in K \quad (23)$$

$$u_{ijk} \geq 0, \forall i, j \in N, k \in K \quad (24)$$

$$s_{ijk} \geq 0, \forall i, j \in N, k \in K \quad (25)$$

Constraint (2) ensures that each active vehicle is assigned to exactly one depot. Constraints (3) and (4) ensure that each vehicle departs from and returns to its assigned depot, respectively. Constraint (5) guarantees that every customer node is visited exactly once, while constraint (6) ensures that if a vehicle enters a customer node, it must also leave it.

Constraint (7) enforces passenger flow conservation by aligning the number of passengers transported with boarding and alighting demands at each node. Constraint (8) ensures freight flow conservation by matching delivered freight at each customer node to its required demand. Constraints (9) and (10) ensure that passenger and freight flows on each arc do not exceed vehicle capacity.

Constraint (11) models travel time uncertainty by representing the actual travel time c_{ij} on arc (i, j) as a log-normally distributed parameter with mean μ_{ij} and standard deviation σ_{ij} . Constraint (12) defines service time at each node, considering the time needed for passenger alighting, boarding, and freight unloading. Constraint (13) ensures a logical sequence of node visits by accounting for service and travel times. Constraints (14) and (15) link the departure and return times of each vehicle to its routing schedule at the depot. Constraint (16) ensures compliance with hard passenger time windows. Constraint (17) limits the total number of vehicles used. Constraints (18)–(25) define the domains of the decision variables.

3.3. Linear reformulation

The nonlinear terms $\max\{0, bt_i^f - a_{ik}\}$ and $\max\{0, a_{ik} - et_i^f\}$ in the objective function, representing penalty costs for early and late freight deliveries, make the model a mixed-integer nonlinear programming model. These terms can be linearized by introducing auxiliary variables E_{ik} and L_{ik} , reformulating the objective function as:

$$\text{Min } Z = \lambda_1 \sum_{k \in K} \sum_{i \in N} e_{ij} x_{ijk} + \dots + \lambda_5 \sum_{k \in K} \sum_{i \in C} E_{ik} + \lambda_6 \sum_{k \in K} \sum_{i \in C} L_{ik} \quad (26)$$

Subject to additional constraints:

$$E_{ik} \geq bt_i^f - a_{ik}, \quad \forall i \in C, k \in K \quad (27)$$

$$L_{ik} \geq a_{ik} - et_i^f, \quad \forall i \in C, k \in K \quad (28)$$

$$E_{ik}, L_{ik} \geq 0, \quad \forall i \in C, k \in K \quad (29)$$

These constraints ensure that E_{ik} and L_{ik} capture the early and late deviations, respectively, transforming the model into a MILP version.

4. Solution approach

This section presents a hybrid solution algorithm, PSA-GA, developed to solve the DR-IPFVRP effectively. Its performance is also examined using exact optimization for small- and medium-scale instances and by comparison with well-established metaheuristics (GA, PSO, and GWO; see Appendix B for details) for large-scale instances.

The Gurobi solver is used to obtain exact benchmark solutions for small- and medium-scale instances that can be solved to global optimality. This enables us to validate the solution quality of the metaheuristics and quantify their corresponding optimality gaps relative to the exact solutions. However, exact optimization becomes computationally impractical for larger DR-IPFVRP instances due to the rapid growth of routing, scheduling, and passenger/freight flow variables. Therefore, for large-scale instances, the metaheuristics are compared using relative performance indicators, particularly the Relative Percentage Deviation (RPD) from the best solution found across all tested metaheuristics (GA, PSO, GWO, and the proposed PSA-GA), which is a common practice in the literature (e.g., Goodarzi et al., 2022; Hajiaghayi-Keshetli et al., 2023; Sadrani et al., 2025). In this way, the exact method provides validation and benchmarking, while metaheuristics provide a practical solution approach for solving large-scale practical instances.

4.1. Hybrid algorithm

This section explains PSA-GA, a hybrid approach that synergistically integrates a PSA algorithm with a GA. Specifically, the method leverages the probabilistic acceptance of non-improving solutions inherent to PSA, combined with the parent selection and crossover

operators of GA, to enhance the search process and achieve a better balance between exploration and exploitation.

The SA, initially introduced by Kirkpatrick et al. (1983), is a popular metaheuristic inspired by the annealing process in metallurgy. The standard SA, as a single solution-based algorithm, focuses on generating a single neighboring solution in each iteration to improve the current solution. In contrast, the PSA generates and handles a population of neighboring solutions around the initial solution, enabling more extensive search space exploration during the optimization process (Askarzadeh et al., 2016). The effectiveness of the PSA algorithm has been demonstrated in various optimization problems, such as multi-retailer inventory routing problems (Shaabani and Kamalabadi, 2016), truck scheduling in multi-door cross-docking systems (Assadi and Bagheri, 2016), and facility layout planning (Forghani et al., 2021).

In our proposed PSA-GA, the process begins with PSA generating a population of neighboring solutions around the initial solution using various operators, including swapping⁵ and inversion⁶ operators (see Fig. 2). Next, GA's diversity-enhancing capabilities are incorporated into PSA to generate new solutions (offspring). This step applies parent selection and crossover operators to the neighboring solutions previously produced by PSA (see Fig. 3 for an illustration of the PSA-GA search procedure). A roulette wheel selection method is employed for parent selection, favoring elite solutions (Katoch et al., 2021). For crossover, a one-point order-based approach is used, as detailed in the GA section (see Appendix B).

As shown in Fig. 3, after generating the offspring, the best member in the offspring population (y'_{best}) is compared with the best member in the neighboring population (y_{best}) according to the SA rule. This rule, which probabilistically accepts non-improving solutions, determines the current solution for continuing the search process (see Fig. 4 for the PSA-GA pseudo code). In this regard, the SA strategy offers an opportunity to accept non-improving solutions, depending on temperature and solution value differences. During early iterations with higher temperatures, there is a greater likelihood of accepting non-improving solutions. As iterations progress and temperatures decrease, the probability of accepting non-improving solutions diminishes, shifting the focus toward exploitation-based search efforts.

4.2. Computational experiments

This section presents the computational experiments conducted to evaluate the effectiveness of the proposed solution algorithms across a diverse set of test instances, including small-, medium-, and large-scale problems. To this end, 30 test instances of various sizes are generated using uniformly distributed random data (see Appendix C for details on the data generation process). A Taguchi method is also applied to fine-tune the algorithm parameters, as described in Appendix D.

Small- and medium-scale instances are solved to optimality using the Gurobi solver, enabling a direct comparison with the solutions obtained by our metaheuristic. The optimality gap is calculated as follows:

$$GAP = \frac{Heu_{sol} - Gurobi_{sol}}{Gurobi_{sol}} \times 100 \quad (30)$$

where $Gurobi_{sol}$ denotes the optimal answer identified by Gurobi, and Heu_{sol} denotes the answer discovered by the chosen metaheuristic.

Each test problem is solved 20 times by the metaheuristics. Table 3 reports the results, including the average and standard deviation of OFVs, as well as the average CPU times. All computations are performed on a personal computer with an Intel(R) Core(TM) i5-6500 CPU @ 3.20 GHz and 16.0 GB RAM. The reported gap values are based on the average OFVs obtained across the 20 runs.

As shown in Table 3, even for small instances, solving the problem with Gurobi requires significantly long CPU times. In contrast, the metaheuristics demonstrate their ability to generate high-quality (optimal or near-optimal) solutions within reasonable CPU times. Among them, the proposed PSA-GA provides the best overall performance, matching Gurobi's optimal solutions in 18 out of 20 instances, with only marginal gaps of 0.08% and 0.14% observed in instances M2 and M6, respectively (see Table 3). Therefore, the average optimality gap across all instances is just 0.01% (0.0001), indicating that PSA-GA achieves solution quality comparable to Gurobi, while requiring significantly less computational effort.

For large-scale instances, where Gurobi becomes computationally impractical, we adopt the RPD metric to evaluate the performance of the metaheuristics. The best solution found across all metaheuristics is used as the reference for computing RPD values:

$$RPD = \frac{Heu_{sol} - Min_{sol}}{Min_{sol}} \times 100 \quad (31)$$

where Heu_{sol} denotes the answer discovered by the chosen algorithm, and Min_{sol} denotes the best-ever answer identified across all the algorithms (GA, PSO, GWO, and PSA-GA).

The results presented in Table 4 demonstrate the superior performance of PSA-GA, which outperforms all other heuristics by achieving an RPD of zero across all test instances. To facilitate visual comparison, the algorithms' outcomes, including CPU times and solution gaps, are also illustrated in Figs E.1 and E.2, respectively (see Appendix E).

To assess the reliability of the algorithms, we also examine the variability of their solutions by analyzing the standard deviation over multiple runs (see Tables 3 and 4). The findings confirm that PSA-GA not only delivers superior performance but also exhibits

⁵ The swapping operator functions by selecting two elements at random and repositioning them.

⁶ The inversion operator functions by randomly choosing a string of elements and reversing their order.

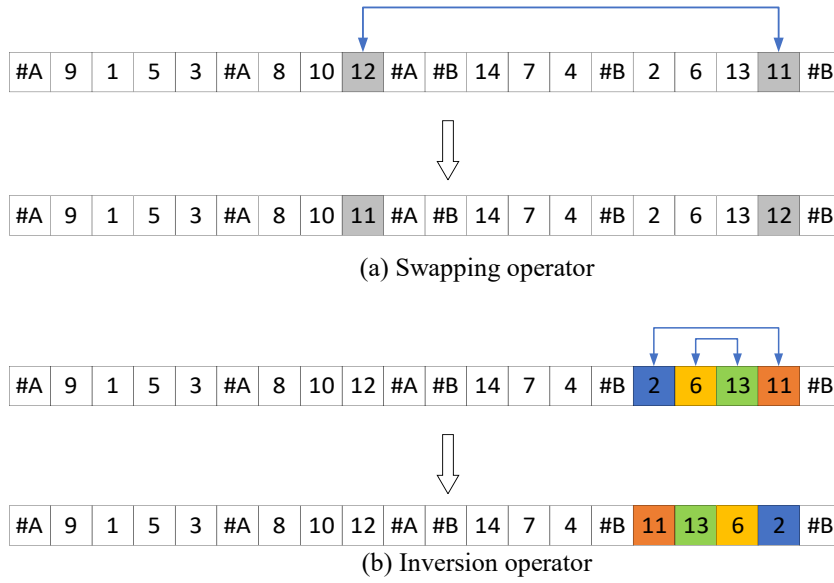
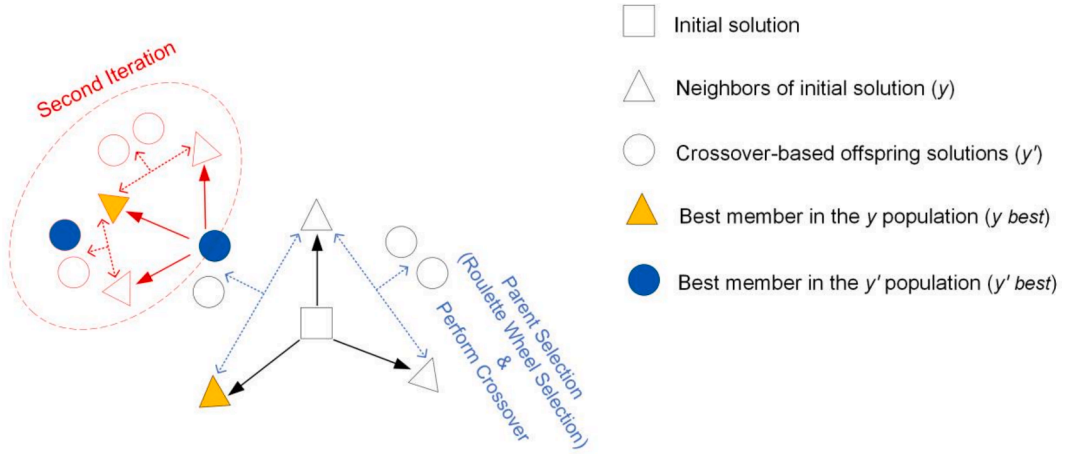


Fig. 2. An example of generating neighboring solutions.



Comparing ● (y' best) and ▲ (y best) based on the SA strategy to determine whether to continue the search process (neighbors production) with ● or ▲ :

Compute $\Delta = \text{Cost}(y'_{best}) - \text{Cost}(y_{best})$
If $\Delta < 0$ or $r = \text{random}(0,1) \leq P = e^{\frac{-\Delta}{T_t}}$ **then**
 Continue with y'_{best}
Otherwise
 Continue with y_{best}
End

Fig. 3. An illustration of the search strategy in the PSA-GA.

```

Initialize neighbor population size ( $Nbor_{pop}$ ), maximum number of iterations
( $MaxIt$ ), crossover rate ( $P_c$ ), initial temperature ( $T_1$ ), cooling rate ( $\alpha$ )

Generate an initial solution and evaluate its objective function value
Set iteration counter  $t = 1$ 

while ( $t < MaxIt$ )
    Generate the neighbor population and evaluate the members
    Get the best member in the neighbor population as  $y_{best}$ 
    Select parents from the neighbor population using a roulette wheel selection
    method
    Apply crossover to the selected parents to create new offspring and evaluate
    them
    Get the best member in the offspring population as  $y'_{best}$ 
    Compare  $y'_{best}$  and  $y_{best}$  based on the SA strategy to determine the current
    solution for continuing the search process (neighbor production):
    Compute  $\Delta = \text{Cost}(y'_{best}) - \text{Cost}(y_{best})$ 
    if  $\Delta < 0$  or  $r = \text{random}(0,1) \leq P = e^{\frac{-\Delta}{T_t}}$  then
        Continue with  $y'_{best}$ 
    otherwise
        Continue with  $y_{best}$ 
    end
    Update and store the cost of the best solution
    Reduce the temperature  $T_{t+1} = \alpha \times T_t$ 
     $t = t + 1$ 
end

```

Fig. 4. Pseudo code of the PSA-GA.

greater stability, providing a higher confidence level in the reliability and robustness of the obtained solutions. We also conduct a statistical analysis to examine the differences in the performance of our algorithms (in Appendix F).

5. Results and discussion: policy insights and sensitivity analyses

In this section, we widely assess the practical, planning, and policy implications of the IPFT approach implemented through DRT services, drawing on a real-world case study in Kirchheim bei München, Germany. We also compare the performance of the proposed IPFT system with that of a segregated passenger-freight transport (SPFT) system. Several sensitivity analyses are conducted to examine the impact of key factors such as cost parameters, passenger and freight demand levels and heterogeneity, and driving time uncertainty. Basic cost parameters and monetary valuations of time are adapted from Sadrani et al. (2022), reflecting the German context (see Table C3 in Appendix C). For emission calculations, the DRT vehicle is represented using the light-duty vehicle category in the COPERT framework. This category is used as a proxy for a minibus-type DRT vehicle with passenger seating and dedicated parcel-storage space, consistent with the IPFT setting considered in the case study. For each network arc, the average operating speed is calculated by dividing the arc distance by the corresponding mean travel time, estimated from historical travel-time data. These arc-level speeds are then used in the COPERT speed-dependent emission functions to estimate distance- and speed-dependent emissions.

The case study network includes two depots and thirty-eight customer nodes, and a typical eight-hour operational day is simulated across four two-hour time periods. Passenger origin-destination data are based on anonymized historical records provided by the local transport operator in Kirchheim bei München. Due to confidentiality agreements, these data cannot be publicly disclosed. Based on this information, we estimate a total daily passenger demand of 588 passengers, averaging 3.87 passengers per node per time period. Freight demand, specifically for parcel deliveries, is synthesized to reflect typical e-commerce delivery patterns in suburban Germany, resulting in 161 parcels per day, or 1.06 parcels per node per period. We relied on indicative figures and trends reported in the KEP-Studie 2023 by the Bundesverband Paket- und Expresslogistik (BIEK, 2023). A more detailed description of the spatial and temporal demand representation used in the case study, including aggregated demand distributions and the individual-node passenger and

Table 3
Results of solving small (S) and medium (M) sized test instances.

Instance ID	Gurobi		GA		CPU time [s]	PSO		CPU time [s]	GWO		CPU time [s]	PSA-GA		CPU time [s]	GAP (%) relative to Gurobi			
	OFV	CPU time [s]	Avg. OFV	SD. OFV		Avg. OFV	SD. OFV		Avg. OFV	SD. OFV		Avg. OFV	SD. OFV		GA	PSO	GWO	PSA-GA
S1	290.97	483.52	290.97	0.00	32.52	290.97	0.00	46.51	290.97	0.00	24.91	290.97	0.00	23.65	0.00	0.00	0.00	0.00
S2	321.64	557.56	321.64	0.00	41.09	321.70	0.04	46.54	321.64	0.00	29.32	321.64	0.00	31.13	0.00	0.02	0.00	0.00
S3	383.36	1381.25	383.78	0.22	50.63	383.71	0.06	61.03	383.36	0.00	32.05	383.36	0.00	31.20	0.11	0.09	0.00	0.00
S4	398.70	1531.02	399.65	0.51	54.21	400.77	0.35	65.44	399.11	0.19	35.17	398.7	0.00	35.72	0.24	0.52	0.10	0.00
S5	436.35	3287.53	439.18	0.71	56.19	440.32	1.17	68.72	437.16	0.25	36.59	436.35	0.00	42.34	0.65	0.91	0.18	0.00
S6	456.63	3723.22	462.02	0.89	56.68	461.15	1.67	70.07	456.63	0.00	37.49	456.63	0.00	43.35	1.18	0.99	0.00	0.00
S7	476.92	4686.57	484.26	1.34	64.58	487.46	2.58	78.69	478.63	0.21	39.06	476.92	0.00	44.48	1.54	2.21	0.36	0.00
S8	503.51	5679.52	508.95	1.43	68.63	510.91	2.94	83.89	506.08	0.29	41.88	503.51	0.00	42.20	1.08	1.47	0.51	0.00
S9	528.65	6717.85	538.96	1.10	71.49	540.23	2.96	94.55	532.76	0.62	43.18	528.65	0.00	46.03	1.95	2.19	0.78	0.00
S10	557.86	7293.99	568.18	1.64	76.91	564.16	2.65	100.06	559.28	0.58	58.12	557.86	0.00	50.85	1.85	1.13	0.26	0.00
M1	579.81	8339.66	586.82	1.66	79.79	593.20	2.70	101.44	584.38	0.84	59.25	579.81	0.00	61.83	1.21	2.31	0.79	0.00
M2	604.08	9505.78	617.97	2.12	92.68	610.96	3.08	104.79	610.11	1.05	69.26	604.56	0.10	65.81	2.30	1.14	0.99	0.08
M3	634.26	10280.9	646.12	3.08	92.89	653.66	3.18	114.71	639.56	0.95	73.26	634.26	0.00	70.10	1.87	3.06	0.83	0.00
M4	665.92	-	674.84	4.75	98.33	690.09	4.05	115.36	673.41	1.12	80.37	665.92	0.00	76.58	1.34	3.63	1.12	0.00
M5	673.06	-	684.63	4.90	98.58	691.36	3.90	121.42	681.80	1.46	80.38	673.06	0.00	85.22	1.72	2.72	1.29	0.00
M6	710.11	-	730.84	5.56	99.95	721.89	3.64	125.49	717.85	1.32	82.81	711.10	0.18	88.49	2.92	1.66	1.09	0.14
M7	759.80	-	778.18	5.63	100.27	777.19	4.07	126.48	773.55	2.31	85.28	759.8	0.00	88.65	2.42	2.29	1.81	0.00
M8	812.94	-	837.82	3.22	111.61	828.95	4.68	130.10	824.73	1.96	88.61	812.94	0.00	92.33	3.06	1.97	1.45	0.00
M9	852.09	-	868.02	3.95	116.19	880.72	4.84	130.66	865.33	2.69	92.08	852.09	0.00	102.13	1.87	3.36	1.55	0.00
M10	878.83	-	898.07	4.33	121.01	907.48	5.58	131.67	891.98	2.66	102.56	878.83	0.00	104.68	2.19	3.26	1.49	0.00
Avg. gap %															1.48	1.75	0.73	0.01
Max. gap %															3.06	3.63	1.81	0.14

*The Gurobi's CPU times exceed three hours.

Table 4
Results of solving large (L) sized test instances.

Instance ID	GA			PSO			GWO			PSA-GA			RPD (%) relative to the best metaheuristic			
	Avg. OFV	SD. OFV	CPU time [s]	Avg. OFV	SD. OFV	CPU time [s]	Avg. OFV	SD. OFV	CPU time [s]	Avg. OFV	SD. OFV	CPU time [s]	GA	PSO	GWO	PSA-GA
L1	1200.68	5.28	126.75	1193.89	6.84	131.95	1189.38	3.49	103.50	1176.12	0.00	105.71	2.08	1.51	1.12	0.00
L2	1314.74	7.19	127.24	1316.89	7.28	134.33	1267.71	3.66	112.32	1249.08	0.06	109.14	5.25	5.42	1.49	0.00
L3	1374.78	7.98	132.10	1384.89	9.18	135.41	1330.22	5.13	114.85	1315.30	0.27	113.11	4.52	5.29	1.13	0.00
L4	1399.01	8.50	132.76	1410.21	9.59	141.98	1365.82	4.03	117.52	1338.38	0.00	119.67	4.52	5.36	2.05	0.00
L5	1852.49	7.86	138.72	1872.35	7.84	151.86	1799.47	4.07	122.02	1783.06	1.05	124.67	3.89	5.01	0.92	0.00
L6	1860.36	7.79	141.31	1880.55	8.38	162.01	1802.33	4.11	123.01	1769.87	0.08	127.46	5.11	6.25	1.83	0.00
L7	1932.19	7.85	145.49	1897.84	8.74	163.45	1846.51	3.91	125.17	1823.28	1.18	132.31	5.97	4.08	1.27	0.00
L8	2099.56	8.97	146.21	2117.74	8.62	167.97	2020.36	6.48	126.59	1994.53	2.56	135.70	5.26	6.17	1.29	0.00
L9	2197.60	8.65	148.46	2222.54	10.08	179.29	2131.94	5.94	129.40	2102.94	0.92	139.33	4.50	5.68	1.37	0.00
L10	2359.94	8.52	159.51	2389.98	9.19	188.23	2310.72	5.51	136.33	2271.91	0.87	141.06	3.87	5.19	1.70	0.00
Avg. RPD %													4.49	4.99	1.41	0.00
Max. RPD %													5.97	6.25	2.05	0.00

freight demand distribution, is provided in Appendix G (Tables G1, G2, and G3).

5.1. Comparison of the IPFT and SPFT systems

In this section, we compare the performance of the IPFT system with that of the SPFT system, where two separate (isolated) fleets independently serve passenger and freight demand. That is, the fleet size is determined separately for passenger and freight requirements in SPFT systems, increasing the total number of operational vehicles in a network. The fleet size and total cost of each system are presented in Table 5. Besides, the cost components of each system are compared in Fig. 5. Overall, the benefits of integration are mostly observed in the reduction of vehicle operating costs (by 34%) and human driving costs (by 33%), illustrating the remarkable capacity of integration in total cost reductions. Moreover, Fig. 5 shows that integrating passenger and freight transport reduces emission costs by 29% compared to the SPFT system, mainly due to the smaller fleet size needed to meet both passenger and freight flows. Nonetheless, two cost components (passengers' trip time costs and time window penalty costs) have witnessed slight rises in the IPFT system. Overall, the integration reduces the total costs by 24%.

It is important to mention that, beyond these operational benefits, the practical implementation of IPFT also requires institutional, regulatory, and vehicle-design readiness. Our proposed model assumes that passengers and parcels are carried in separate compartments, with separate passenger capacity and dedicated parcel-storage capacity. Therefore, the model does not assume that passenger seats and parcel storage are interchangeable. Rather, this assumption should be interpreted as a planning assumption for evaluating the operational potential of IPFT under specified vehicle-capacity conditions.

Real-world implementation would require appropriate vehicle design and operational procedures to ensure that parcel transport does not compromise passenger comfort, accessibility, safety, or service reliability. Vehicles may require dedicated parcel compartments, secure loading areas, and handling procedures that minimize dwell time and avoid interference with passenger boarding and alighting. From an institutional and regulatory perspective, implementation requires clear agreements on liability, insurance, data exchange, labor responsibilities, service-quality monitoring, and cost/revenue sharing between public transport authorities, DRT operators, municipalities, and logistics providers. Regulatory frameworks may also determine whether public transport vehicles are allowed to carry commercial parcels, under which safety and service conditions this is permitted, and how public service obligations are protected. These considerations suggest that IPFT should not be interpreted only as a routing and scheduling problem, but also as a governance and implementation challenge. This is consistent with Bruzzone et al. (2021), who highlight that institutional, regulatory, and operational barriers can strongly influence the feasibility of IPFT systems. Pilot projects, institutional agreements, and regulatory guidance are therefore important prerequisites for translating the operational efficiency gains identified in this study into real-world practice.

5.2. Occupancy levels

To provide further insight into vehicle utilization, Table 6 reports the average passenger occupancy, freight load utilization, and combined vehicle utilization for the IPFT and SPFT systems. Passenger occupancy is calculated as passenger-kilometers served divided by total available passenger-seat-kilometers [Eq. (32)]. Freight load utilization is calculated as parcel-kilometers served divided by total available parcel-capacity-kilometers [Eq. (33)]. Moreover, combined utilization is calculated as the average of passenger occupancy and freight load utilization, where both service dimensions are present.

$$\text{Passenger occupancy} = \frac{\sum_{k \in K} \sum_{i \in N} \sum_{j \in N, j \neq i} U_{ijk} d_{ij}}{P \sum_{k \in K} \sum_{i \in N} \sum_{j \in N, j \neq i} x_{ijk} d_{ij}} \quad (32)$$

$$\text{Freight load utilization} = \frac{\sum_{k \in K} \sum_{i \in N} \sum_{j \in N, j \neq i} S_{ijk} d_{ij}}{F \sum_{k \in K} \sum_{i \in N} \sum_{j \in N, j \neq i} x_{ijk} d_{ij}} \quad (33)$$

The IPFT and SPFT systems have different optimized fleet sizes; therefore, the utilization indicators should be interpreted as system-level measures of capacity use under each optimized service configuration rather than direct one-to-one vehicle occupancy comparisons. The results show that the IPFT shared fleet achieves higher combined utilization than the SPFT system overall. Interestingly, the passenger occupancy of the IPFT fleet is slightly lower than that of the SPFT passenger-only fleet. This reflects the shared routing structure of IPFT, where passenger demand is served within a fleet that also accommodates parcel deliveries. As a result, passenger demand may be distributed across more vehicle movements, and some route segments or service times are influenced by parcel delivery. This can increase available passenger-seat-kilometers without a proportional increase in passenger-kilometers, leading to

Table 5
Comparative assessment of the IPFT and SPFT systems.

Scenario	Fleet size (veh)	Total costs (€)
IPFT system	12	1796.1
SPFT system	18*	2352.8

*Among 18 vehicles, 10 vehicles are used for passenger-related services, and 8 of them for freight services.

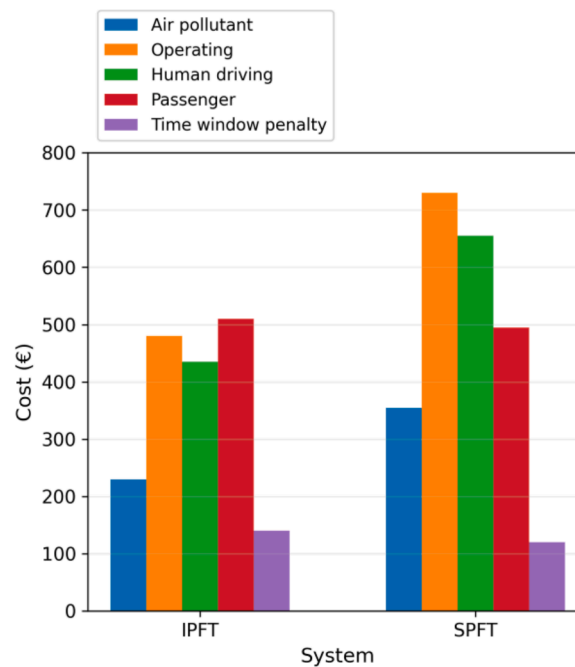


Fig. 5. Cost components of the IPFT and SPFT systems.

Table 6

Occupancy and utilization indicators in IPFT and SPFT systems.

Scenario	Optimal fleet size	Avg. passenger occupancy	Avg. freight load utilization	Avg. combined utilization
IPFT shared fleet	12	32.6%	37.4%	35.0%
SPFT passenger fleet	10	34.1%	—	34.1%
SPFT freight fleet	8	—	25.8%	25.8%
SPFT system overall	18	34.1%	25.8%	30.0%

slightly lower passenger occupancy.

However, freight load utilization is higher in the IPFT system than in the SPFT freight-only fleet, and the combined utilization is also higher. The higher freight load utilization in IPFT can be explained by the joint routing structure. The model builds joint routes where passenger trips remain the primary service, and parcel deliveries are inserted into those routes when this is operationally beneficial and feasible. As a result, parcels may be carried over parts of passenger-serving routes, leading to a moderate increase in freight load utilization compared with the SPFT freight-only fleet.

These results suggest that the advantage of IPFT comes from improved overall vehicle utilization rather than from higher passenger occupancy alone. These findings help interpret the sensitivity analysis that when vehicle resources are used more intensively, changes in demand can have a stronger effect on routing flexibility, service feasibility, and fleet requirements. It should be noted that passenger and freight capacities are represented as separate capacity dimensions. Therefore, combined utilization is reported only as an aggregate indicator of average capacity use across the two dimensions and does not imply that passenger seats and parcel storage are interchangeable.

5.3. Sensitivity to cost factors

In this section, we evaluate the sensitivity of fleet size solutions in an IPFT system to variations in cost parameters, recognizing that economic and location-based factors can significantly influence these monetary values. The cost parameters are decreased and increased by $\pm 20\%$, $\pm 40\%$, and $\pm 60\%$, as illustrated in Fig. 6. For example, since the base case cost values are evaluated for Germany, reducing vehicle operating and human driving cost parameters allows us to explore how the solutions might change in medium- and low-income countries.

As shown in Fig. 6, the fleet size of an IPFT system is most impacted by the passenger trip time value, followed by vehicle operating and human driving costs. For instance, the fleet size grows by 33% (going from 12 to 16 vehicles) when the value of passengers' trip time savings increases by 60%. The findings from a decline in the costs associated with human driving can be interpreted as a cost scenario in which an IPFT system is operated by an autonomous fleet of vehicles. In Fig. 6 (c), we assess the sensitivity of solutions in an IPFT system to emission costs by reducing/increasing the base cost of unit air pollutants by 20%, 40%, and 60%. For example, the

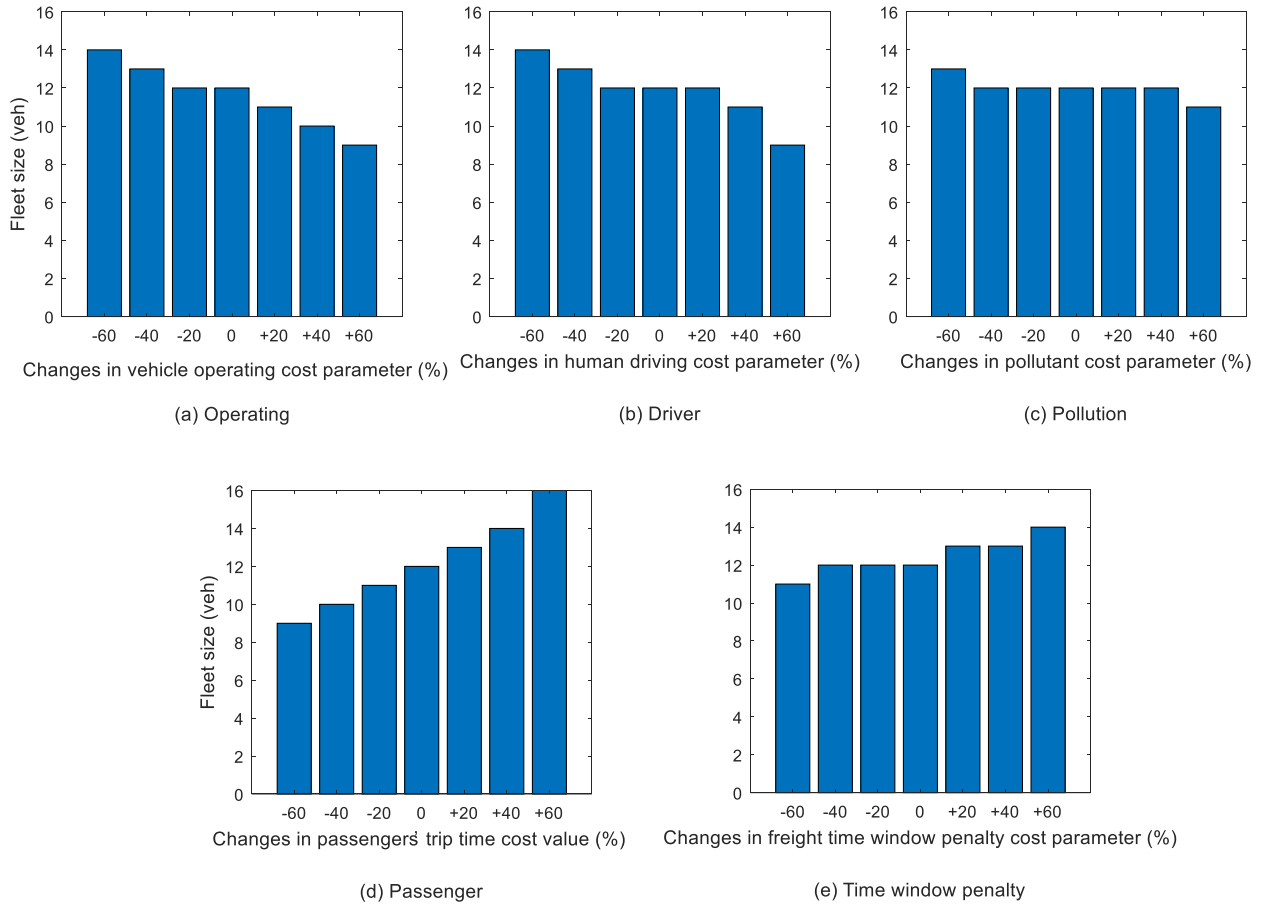


Fig. 6. Sensitivity of solutions to various cost components.

results indicate that a 60% increase in emission costs reduces the fleet size from 12 to 11 vehicles, while a 60% decrease in emission costs increases the fleet size from 12 to 13 vehicles.

Our cost assessments show that, by reducing operating costs for service providers, the overall cost balance conditions allow for increasing service frequencies in an IPFT system by deploying a larger fleet size⁷, thereby enhancing service quality for users by reducing both passengers' trip times and time window penalty costs. Fig. 7 displays the potential cost reductions for users due to a larger fleet size. For example, increasing the fleet size from 12 to 14 vehicles (which is reachable with a 60% decrease in human-related driving costs) can reduce time window penalty costs by about 50%. This improvement occurs because, with a larger fleet, each vehicle is responsible for fewer deliveries, allowing them to reach their destination nodes more punctually. Moreover, error bars in Fig. 7 and subsequent simulation-based cost figures represent standard deviations from repeated Monte Carlo simulation evaluations (see Appendix H) under stochastic travel-time conditions.

5.4. Sensitivity to demand level

In this part, we assess the fleet size solutions' sensitivity to changes in the demand levels of passenger and freight items, for both IPFT and SPFT systems. For this issue, in the first set of assessments, we increase/decrease the passenger demand by $\pm 20\%$, $\pm 40\%$, and $\pm 60\%$, while the freight demand remains unchanged. The same test is carried out for the freight demand in the second set of assessments. As can be observed in Fig. 8, the fleet size solutions in both IPFT and SPFT systems are more sensitive to the passenger demand than the freight demand, which can be explained by the fact that trip time savings for passenger groups are valued more highly by policymakers than on-time freight deliveries. Besides, the solutions in an IPFT system exhibit greater robustness (less variation) to changes in demand levels. For example, in response to a 40% rise in passenger demand, the IPFT system's fleet size increases by 16%

⁷ In this situation, operating costs increase at a lower rate as the fleet size grows, while the reduction in passengers' trip time costs and time window penalty costs becomes more dominant due to a larger fleet size, thus creating a more balanced situation with greater advantages for the system.

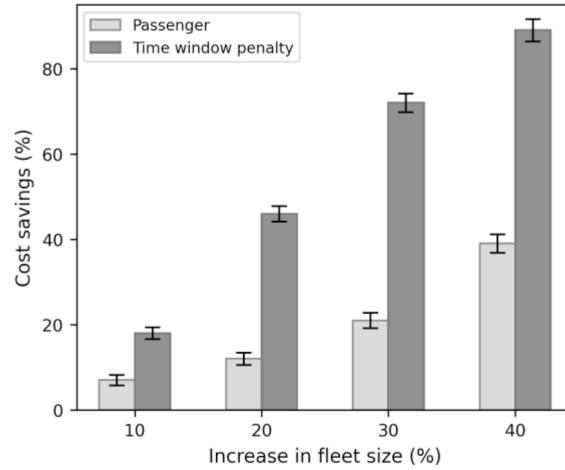


Fig. 7. Potential cost savings for system users.

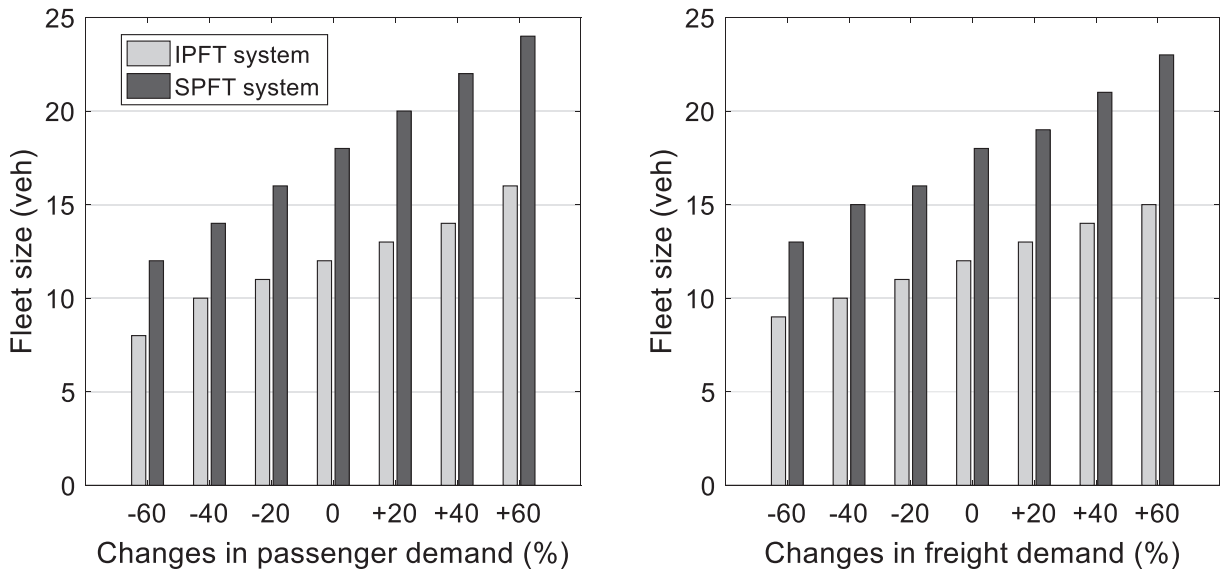


Fig. 8. Sensitivity to demand levels.

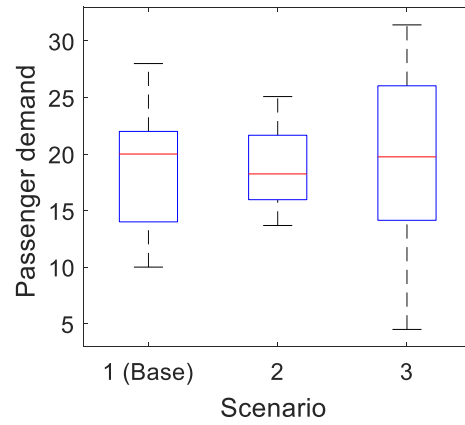
(going from 12 to 14 vehicles), while the SPFT system's fleet size increases by 22% (going from 18 to 22 vehicles).

5.5. Sensitivity to demand heterogeneity

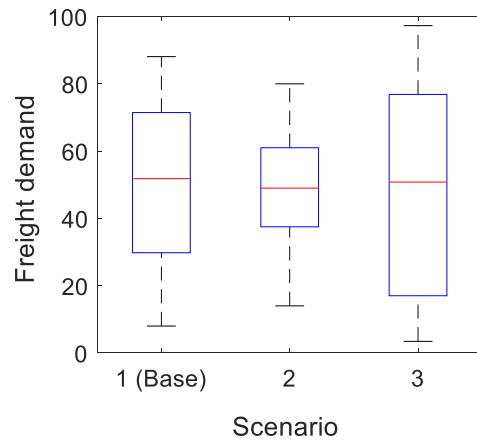
In this part, we assess the sensitivity of solutions to demand heterogeneity for both IPFT and SPFT systems. For the base case analysis, a typical eight-hour workday was simulated across four two-hour time periods, during which demand fluctuates across different nodes. Fig. 9 presents the degree of demand heterogeneity across nodes in the base case scenario (scenario 1). We then explore two additional scenarios (scenarios 2 and 3), where demand heterogeneity is reduced and increased, respectively, while keeping the total demand level constant across all scenarios. As illustrated in Fig. 10, our results indicate that the IPFT system is more sensitive to changes in demand heterogeneity. For instance, in scenario 3, which features more dispersed demand patterns, the fleet size for the IPFT system changes by 8.3%, whereas the fleet size for the SPFT system remains unchanged.

5.6. Sensitivity to temporal demand alignment

In this part, we investigate the temporal alignment between passenger and freight demand, which can influence the relative performance of IPFT and SPFT systems. This issue is particularly relevant for DRT-based integration because passenger demand may be concentrated during peak periods, whereas parcel delivery demand may be more flexible and partly shiftable to off-peak passenger



(a) Passenger demand dispersion within nodes



(b) Freight demand dispersion within nodes

Fig. 9. Demand heterogeneity patterns.

periods. To examine this effect, we conduct an additional sensitivity analysis with alternative temporal demand distributions while keeping total daily passenger and freight demand unchanged.

Three temporal demand scenarios are considered. The first scenario corresponds to the base case, which already exhibits moderate temporal complementarity, with passenger demand concentrated in the first and fourth operating periods and freight demand more concentrated in the middle periods (as shown in Table G1). The second scenario represents stronger temporal complementarity, where freight demand is shifted further toward off-peak passenger periods. The third scenario represents an overlapping-peak structure, where both passenger and freight demand are concentrated in the same high-demand periods. These scenarios allow us to assess whether the benefits of integration depend on the temporal compatibility between passenger and freight services.

The results in Table 7 show that stronger temporal complementarity strengthens the benefits of IPFT. Under the stronger complementarity scenario, the IPFT system requires fewer vehicles and achieves the largest cost reduction compared with SPFT. This occurs because freight deliveries can be assigned to periods in which passenger demand is relatively lower, allowing better use of vehicle capacity with fewer conflicts with passenger service requirements. By contrast, when passenger and freight demand peak in the same periods, the advantage of IPFT decreases because both demand types compete for vehicle capacity and scheduling flexibility. Nevertheless, IPFT remains beneficial in the tested scenarios, although the magnitude of cost and fleet-size reductions is lower under overlapping demand peaks. These findings indicate that temporal demand management can be an important policy lever for implementing IPFT. For example, public transport authorities and logistics partners could coordinate delivery time windows to encourage parcel deliveries during off-peak passenger periods.

5.7. Sensitivity to driving time uncertainty

Here, we examine the sensitivity of solutions to driving time uncertainty. The stochastic nature of driving times between nodes may be influenced by various aspects, including traffic conditions, road types, weather, and the heterogeneity of human driving behaviors. The driving time between nodes i and j (c_{ij}) is sampled by means of a log-normal distribution function (see Appendix H), i.e.,

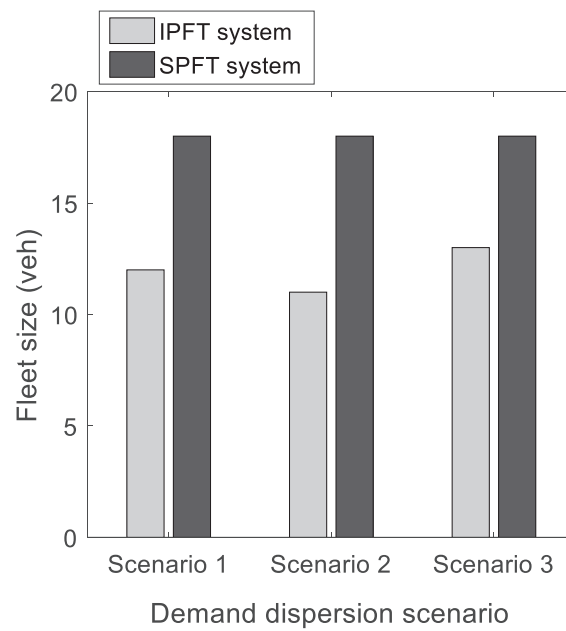


Fig. 10. Sensitivity to demand heterogeneity.

Table 7

Sensitivity to the temporal alignment between passenger and freight demand.

Scenario	Description	IPFT fleet size	SPFT fleet size	IPFT total cost (€)	SPFT total cost (€)	Cost reduction of IPFT
Scenario 1	Base case: moderate temporal complementarity	12	18	1796.1	2352.8	23.7%
Scenario 2	Strong complementarity: freight shifted to passenger off-peak periods	11	18	1715.4	2341.2	26.7%
Scenario 3	Overlapping peaks: passenger and freight demand peak simultaneously	13	18	1908.6	2368.5	19.4%

Note: Total daily passenger and freight demand are kept constant across all scenarios; only their temporal distribution is changed.

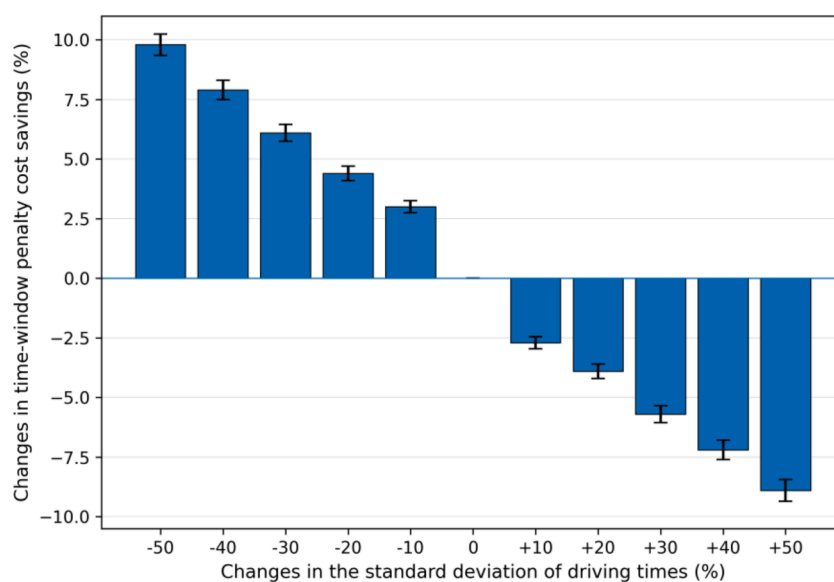


Fig. 11. Sensitivity to driving time uncertainty.

c_{ij} Lognormal (o_{ij}, σ_{ij}) , where o_{ij} and σ_{ij} stand for the mean and standard deviation of driving time between nodes i and j , respectively.

We conduct a sensitivity test on the volatility of driving times at different arcs to examine its impact on the timely completion of delivery tasks, measured by time window penalty costs for early and late arrivals. To this end, we increase or decrease the standard deviation of driving times by 10-50%. For example, as illustrated in Fig. 11, the time window penalty costs decrease by 9.8% when the driving time volatility reduces by 50%.

6. Concluding remarks

This study explored the potential of Integrated Passenger-Freight Transport (IPFT) within the framework of Demand-Responsive Transport (DRT) services by introducing the Demand-Responsive Integrated Passenger-Freight Vehicle Routing Problem (DR-IPFVRP). The DR-IPFVRP addresses the routing and scheduling of shared DRT vehicles to serve both passenger and freight demand in a transport network, with a particular application focusing on rural areas. A Mixed-Integer Linear Programming (MILP) model was developed to minimize total system costs, explicitly capturing vehicle and driver operating costs, emissions (CO₂ and primary air pollutants), passenger travel time costs, and penalties for freight time window violations. The model also accounted for the differing time sensitivities and priority requirements of passenger and freight transport (Cappelli and Nocera, 2006), aligning with public transport regulations that prioritize passenger reliability.

To address the model's computational complexity, we developed a hybrid metaheuristic algorithm, PSA-GA, which integrates Population-based Simulated Annealing (PSA) with parent selection and crossover mechanisms from a Genetic Algorithm (GA). Computational experiments on small- to large-scale instances confirmed the superior performance of PSA-GA in terms of solution quality and computational efficiency.

We broadly examined the planning and policy implications by applying the DR-IPFVRP model to a real-world case study in Kirchheim bei München, Germany. Supported by extensive sensitivity analyses, our findings demonstrated that implementing IPFT through flexible DRT services can significantly reduce system costs compared to conventional SPFT systems. Overall, our principal findings are summarized as follows:

- In a DRT setting, IPFT reduces total system costs by 24% relative to a conventional SPFT system, mainly due to lower fleet-size requirements and reductions in vehicle operating costs (34%), human driving costs (33%), and pollution-related costs (29%).
- Fleet size in an IPFT system is most influenced by the value of passengers' travel time, followed by vehicle operating and labor costs. For instance, a 60% increase in the value of passengers' time results in a 33% increase in required fleet size.
- Reducing service providers' operating costs enables the deployment of a larger fleet size, which improves service quality by reducing passenger travel time and freight delivery time window violations.
- Fleet sizing in both IPFT and SPFT systems is more sensitive to passenger demand than freight demand. However, IPFT solutions are less sensitive to overall demand levels but more sensitive to demand heterogeneity.
- The performance of the IPFT system is more strongly linked to overall vehicle utilization than to passenger occupancy alone. Although passenger occupancy in the shared IPFT fleet is slightly lower than in the SPFT passenger-only fleet, the integrated system achieves higher combined utilization through its joint routing structure, which also explains its stronger sensitivity to changes in passenger and freight demand.
- The benefits of IPFT are also influenced by temporal demand alignment. When freight demand is shifted toward off-peak passenger periods, the integrated system achieves greater cost savings and requires fewer vehicles. In contrast, overlapping passenger and freight peaks reduce the integration advantage.
- Reducing travel time variability by 50% leads to a 9.8% reduction in time window penalty costs, highlighting the importance of operational reliability.

This study opens several avenues for future research. The model could be extended to incorporate emerging vehicle technologies, such as automated vehicles, which may reshape cost structures by reducing driver-related costs. Furthermore, applying the framework to diverse socio-economic and geographic contexts could provide further insights into its generalizability and policy relevance beyond the German case study. To explore implementation challenges, a multi-criteria decision-making (MCDM) framework could be employed to identify and prioritize key barriers to the adoption of passenger-freight integration in DRT systems, such as regulatory constraints, institutional fragmentation, and stakeholder resistance (see Sadrani et al., 2024, for further insights into the MCDM method). Moreover, in the present study, passenger and freight demand are treated as exogenous inputs to the routing and scheduling model. This assumption allows the analysis to focus on the operational efficiency of integrated services under specified demand conditions. However, real-world adoption of IPFT-based DRT services may depend on behavioral and commercial responses. Passenger demand may vary with perceived reliability, travel time, comfort, fare levels, and willingness to share vehicle space with parcels. Similarly, freight participation may depend on delivery reliability, cost-sharing mechanisms, and contractual agreements between logistics providers and transport operators. Future research could therefore integrate the proposed routing model with demand elasticity, mode-choice, or adoption models to capture feedback between service quality, passenger acceptance, logistics participation, and system efficiency.

Although our current formulation adopts a passenger-first service logic using hard passenger time windows and soft freight time windows, real-world passenger-freight prioritization may include additional complexities beyond deterministic scheduling constraints, such as regulatory obligations, service quality requirements, equity considerations, and operational uncertainty. Hence, future

research could extend our proposed problem by incorporating multi-objective formulations that explicitly balance passenger service quality, freight service performance, operator costs, environmental impacts, and equity. In addition, stochastic modeling approaches, such as chance-constrained programming or stochastic dominance formulations, could be developed to capture uncertainty in demand, travel times, service reliability, and regulatory service thresholds.

CRedit authorship contribution statement

Mohammad Sadrani: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Silvio Nocera:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Constantinos Antoniou:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Conceptualization, Funding acquisition.

Acknowledgments

This research has been supported by the German MCube cluster (COLTOC project, Förderkennzeichen: 03ZU1105KA), funded by the German Federal Ministry for Research, Technology and Space. The authors would also like to thank the anonymous reviewers for their constructive comments and suggestions, which helped improve the manuscript.

Appendix A. Strategic vehicle design for integrated passenger-freight transport

Here, we discuss a strategic design that utilizes the available space within the vehicle. These solutions are implementable on passenger vans, retaining the characteristics and approximate capacity of the passenger cabin while allowing parcel loading capacity in similar values to those of small freight vans typically used by postal services.

Overhead storage compartments: The first solution is using overhead storage compartments (commonly available or implementable in vans configured for suburban and interurban services). Their use can maximize vertical space, providing a secure location for parcels and smaller freight items. These compartments can be accessed easily, ensuring efficient loading and unloading processes.

Underfloor compartments: Another practical option is underfloor compartments for storing pre-prepared packages, utilizing the space beneath the vehicle which is normally not used for luggage on short-distance trips. This solution has been explored for the case of the Italian provinces of Forlì-Cesena ([Cavallaro et al., 2023](#)). It contributes to an overall significant cargo capacity, but also maintains a clear separation between the passengers and the transported goods, ensuring safety, comfort, and compliance with regulatory standards.

Rear vehicle spaces: Purposefully designed spaces in the rear of the vehicle, accessible from the back doors, can be incorporated. These areas can be equipped with shelving or secure fastening mechanisms to organize and protect the parcels during transit. Alternatively, configurations immediately behind or beside the driver's seat can be optimized for both passenger comfort and freight storage, with modular solutions that can be adapted based on specific transportation needs. In the case of low-floor minibuses and vans, which lack underfloor space, these configurations are preferred and also offer the opportunity to fully accommodate standard rolls that can be locked in place and loaded and unloaded rapidly, also resulting in operational benefits and energy savings, mainly due to reduced total mileage and the predisposition to shift to the active modes for the last mile ([Bruzzone et al., 2023b](#)).

By emphasizing these design aspects, we aim to provide an overview of the effectiveness of solutions that balance passenger comfort and freight transport efficiency. This approach not only addresses the feasibility of technical adaptation, but also emphasizes the feasibility of adapting classical vans or minibuses to seamlessly accommodate both passengers and cargo in urban, peri-urban, and rural delivery scenarios. Although it requires normative advancements and, in many cases, physical modifications to the fleets, the integration of passengers and parcels on board vans and minibuses aligns with the broader objective of enhancing operational efficiency and financial sustainability of delivery fleets. This approach also contributes to mitigating the environmental impacts, particularly in urban areas and during periods of low transport demand.

Appendix B. Descriptions of solution algorithms

1) Genetic algorithm

The GA is a famous evolutionary algorithm that uses the idea of evolution and natural selection to manage and improve a population of solutions ([Katoch et al., 2021](#); [Sadrani et al., 2023](#)). Encoding, or solution representation, is an essential step in applying metaheuristics since it allows the specification of solutions for metaheuristics in a comprehensible manner. In this regard, the GA expresses each solution in the form of a chromosome, composed of a set of genes characterizing the decision variables of the problem. An example is presented in Fig. B.1, exhibiting the depot and the sequence of customers covered by each vehicle.

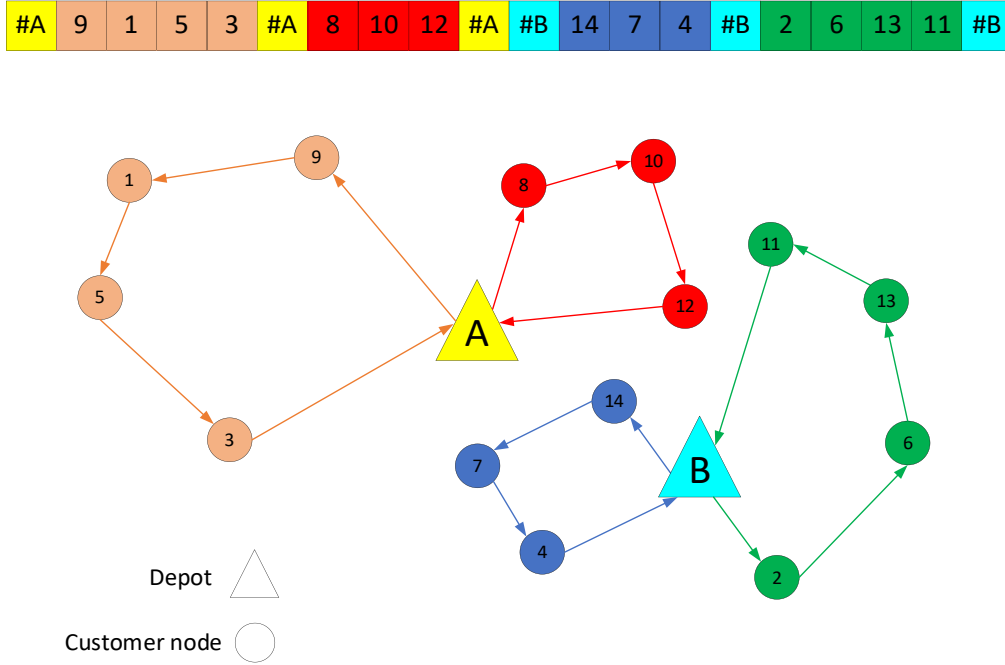


Fig. B.1. An example of solution (chromosome) encoding.

Parent selection, crossover, and mutation are the three fundamental operators in the GA to produce new individuals (offspring), thus promoting population diversity (the GA's steps are summarized in Fig. B.2). We use a one-point order-based crossover, which is a widespread crossover type for permutation-based encoding (Andreica and Chira, 2015), and a swapping mutation operator to promote the diversity of solutions.

To explain the one-point order-based crossover, let us consider two parents: $P_1 = \{a_1, a_2, \dots, a_J\}$ and $P_2 = \{b_1, b_2, \dots, b_J\}$. An integer value u ($1 \leq u < J$) is randomly selected. The first offspring inherits the genes of the first parent from 1 to u (i.e., $\{a_1, \dots, a_u\}$), while the remaining genes are obtained from the second parent such that the genes previously taken from the first parent are not used again (see an example in Fig. B.3). Thus, in this approach, a new sequence (placement) of elements is created without duplicating similar elements in one chromosome to avoid producing infeasible instances (for a thorough review of popular crossover operators for permutation-based problems, see Andreica and Chira, 2015). It should be mentioned that for the parent selection stage, we employ a roulette wheel selection method.

The assessment phase determines the suitability of solutions using the following fitness function:

$$F(x) = \frac{Z_{\max} - Z(x)}{Z_{\max} - Z_{\min}} \quad (B1)$$

where the OFV of chromosome x is denoted by $Z(x)$, and the OFVs for the existing population's worst and best solutions are denoted by $Z_{\max}$ and $Z_{\min}$, respectively. Given that we address a minimization problem in this study, the fitness score of a solution would be higher if it results in a lower cost value, according to Eq. (B1). Finally, the members of the present population and the new children (created by crossover and mutation) are combined to create the next generation, which is then ordered according to fitness ratings. The top N_{pop} individuals are then selected for the upcoming generation.

Initialize population size (N_{pop}), maximum number of iterations ($MaxIt$), crossover rate (P_c), and mutation rate (P_m)

Begin

Generate the initial population of chromosomes Y_i ($i = 1, 2, \dots, N_{pop}$)

Evaluate the fitness of each chromosome in the population by Eq. (B1)

Set iteration counter $t = 1$

while ($t < MaxIt$)

Select parents from the population using a selection method, e.g., roulette wheel selection

Perform crossover on the selected parents with a rate of P_c

Perform mutation on the offspring with a rate of P_m

Evaluate the fitness of the generated offspring by Eq. (B1)

Merge the current population and offspring population (obtained from crossover and mutation), and sort the individuals based on their fitness

Select the best (top) N_{pop} individuals for the next generation

Increase the current iteration by 1, $t = t + 1$.

end

Return the chromosome with the best fitness value, Y_{best} , as the best solution

end

Fig. B.2. Pseudo code of the GA.

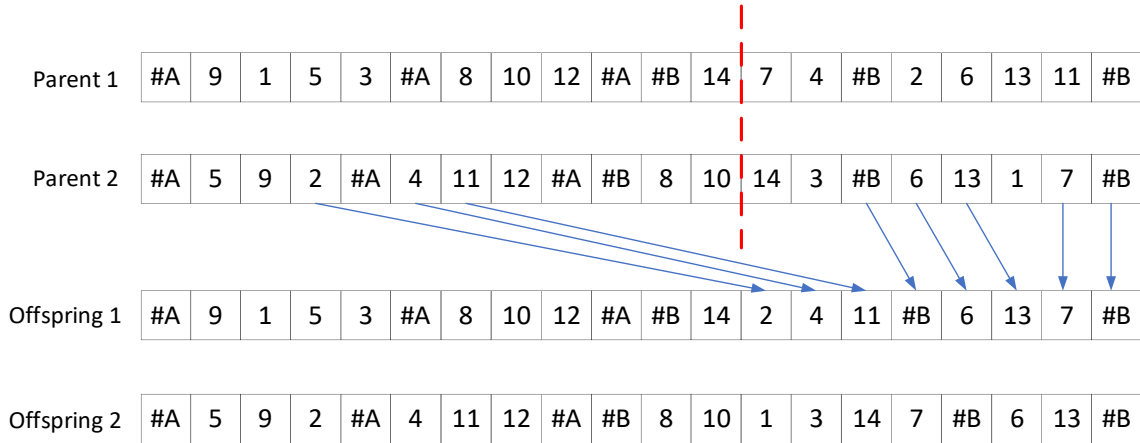


Fig. B.3. An example of one-point order-based crossover.

2) Particle swarm optimization

The PSO is a swarm intelligence algorithm inspired by the collective behavior of birds searching for food (Eberhart and Kennedy, 1995). It employs a swarm of particles, each characterized by its position and velocity, to explore the search space for the best position. The particles adjust their positions and velocities according to the following equations:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (B2)$$

$$v_i(t+1) = w.v_i(t) + c_1.r_1.(pbest_i - x_i(t)) + c_2.r_2.(gbest - x_i(t)) \quad (B3)$$

where t denotes the current iteration, x_i and v_i reflect the position and velocity of the i -th particle. w refers to the inertia weight. c_1 and c_2 represent acceleration coefficients. The best position of the i -th particle and the best position vector in the swarm are denoted by $pbest_i$ and $gbest$, respectively. r_1 and r_2 are uniform random numbers in the range of $[0,1]$. The steps of the PSO algorithm are sum-

marized in Fig. B.4.

```

Initialize population size (Swam_Size), maximum number of iterations (MaxIt),
and acceleration coefficients ( $c_1$  and  $c_2$ )

Begin
  Initialize the population of particles  $x_i$  ( $i = 1, 2, \dots, Swam\_Size$ )
  Initialize the best personal position for each particle,  $pbest_i$ , with the initial position
  Initialize the global best position,  $gbest$ , with the best particle in the initial population
  Set iteration counter  $t = 1$ 
  Evaluate the fitness values of all particles

  while ( $t < MaxIt$ )
    For each particle  $i$ :
      Calculate the particle velocity and position using Eqs. (B2) and (B3)
      If the fitness value is better than the personal best,  $pbest_i$ :
        Update  $pbest_i$  with the current position
      Select the particle with the best fitness value in the swarm as the global best,  $gbest$ 
      Increase the iteration counter,  $t = t + 1$ .
    end
  Return the global best position,  $gbest$ , as the best solution
end

```

Fig. B.4. Pseudo code of the PSO.

3) Grey wolf optimizer

Initially introduced by Mirjalili et al. (2014), GWO is a swarm intelligence algorithm that mimics the social structure and hunting behavior of grey wolves. Its straightforward search procedure and low number of control parameters have made it an appealing choice for a variety of engineering optimization problems, including flow shop scheduling, water resources management, supply chain management, and power dispatch issues (Faris et al., 2018). Despite its growing popularity in these domains, GWO has received limited attention in the transportation planning literature (for a comprehensive review of GWO applications, see Faris et al., 2018; Sharma et al., 2022).

Different steps of the GWO algorithm are detailed next. Overall, the leadership hierarchy in GWO is simulated by considering four types of grey wolves: alpha, beta, delta, and omega. In essence, the alpha wolf (α) refers to the best (most important) individual in a grey wolf pack, known as the group leader. The second and third top individuals are beta (β) and delta wolves (δ), respectively. Other individuals are known as omega (ω) wolves, essentially guided by the α , β , and δ wolves during the search for prey. Moreover, the hunting phase is simulated in three steps: encircling, hunting, and attacking. The GWO's pseudo code is presented in Fig. B.5.

In the early stage of the hunting process, the grey wolves surround their prey during the encircling phase. This behavior can be described mathematically as follows:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (B4)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (B5)$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (B6)$$

$$\vec{C} = 2\vec{r}_2 \quad (B7)$$

where t stands for the current iteration, $\vec{X}_p$ for the prey's location, and $\vec{X}$ for a wolf's location. Vectors $\vec{A}$ and $\vec{C}$ enable wolves to relocate surrounding the prey. A wolf's distance from its prey is represented by D . Furthermore, $\vec{r}_1$ and $\vec{r}_2$ refer to random vectors in the range of $[0, 1]$ (Mirjalili et al., 2014).

In the hunting phase, performed after the encircling phase, the locations of omega (ω) wolves will be updated based on the directions of the α , β , and δ wolves, regarded as the three best solutions identified thus far. The motivation behind this is that the three best search agents (the three best solutions), having a better understanding of the prey's location, can guide the other agents in their

pursuit. This concept is mathematically represented as follows:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right|, \quad \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right|, \quad \vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \quad (\text{B8})$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (\text{B9})$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (\text{B10})$$

To better balance the exploration and exploitation phases, the attack phase simulates how grey wolves approach their prey. When search agents separate from one another in order to find a better prey ($|\vec{A}| > 1$), this reinforces the GWO's exploration. $|\vec{A}| < 1$ instead directs the grey wolves to attack the prey, enhancing the GWO's exploitation. Depending on the parameter $\vec{a}$ that is lowered from 2 to 0, it might vary within the range of $[-2, 2]$.

```

Initialize the grey wolf population  $X_i (i = 1, 2, \dots, n)$ 
Initialize  $a$ ,  $A$ , and  $C$ 
Evaluate the fitness of each search agent
 $X_\alpha$  = the best search agent
 $X_\beta$  = the second best search agent
 $X_\delta$  = the third best search agent
while ( $t < MaxIt$ )
    for each search agent
        Update the position of the current search agent by Eq. (B10)
    end
    Update  $a$ ,  $A$ , and  $C$ 
    Evaluate the fitness of all search agents
    Update  $X_\alpha$ ,  $X_\beta$ , and  $X_\delta$ 
     $t = t + 1$ 
end
Return  $X_\alpha$ 

```

Fig. B.5. Pseudo code of the GWO (Mirjalili et al., 2014).

4) Random-key encoding scheme

Since the PSO and GWO are originally continuous-based metaheuristics, a proper encoding procedure is needed to encode solutions in a way that adapts these algorithms to problems with a discrete search space (Goodarzian et al., 2021; Nayeri et al., 2022). For this purpose, we use the Random-Key (RK) technique, which is a popular encoding method to apply such continuous metaheuristics to discrete search spaces (Fathollahi-Fard et al., 2020; Goodarzian et al., 2022; Kamran et al., 2022). By employing the RK method, we transform the discrete sequence of visits into a continuous representation that can be processed by these algorithms, enabling the optimization process within the DR-IPFVRP.

In our problem, the solution encoding is implemented in two sub-solutions, as detailed below:

(a) The first sub-solution specifies the sequence in which customers are served by each vehicle. Hence, first, a matrix (whose size is equal to the number of customer nodes, i.e., $|C|$ elements) is generated using a uniform distribution $U(1, m + 1)$, where m refers to the fleet size [Fig. B.6 (a)]. Then, the random numbers are sorted in ascending order, representing the sequence in which the customer nodes will be served. Besides, the integer portions of these numbers determine which vehicle will be assigned to serve each customer. For example, according to the encoded solution in Fig. B.6 (a), the sequence of nodes traveled by vehicles 1, 2, 3, and 4 would be as follows:

Vehicle 1: {4→7→5} Vehicle 2: {1→10→3→14}

Vehicle 3: {12→2→8} Vehicle 4: {9→13→11→6}

(b) In the second sub-solution, the dispatching depot for each vehicle is determined. Hence, a matrix with m elements is produced using a uniform distribution $U(0, |D|)$, where $|D|$ refers to the number of depots. The numbers in the matrix are then rounded, indicating the depot from which each vehicle will be dispatched. For example, in Fig. B.6 (b), the encoded number 1.2 (in the first element) is rounded to 2, indicating that vehicle 1 is assigned to depot 2.

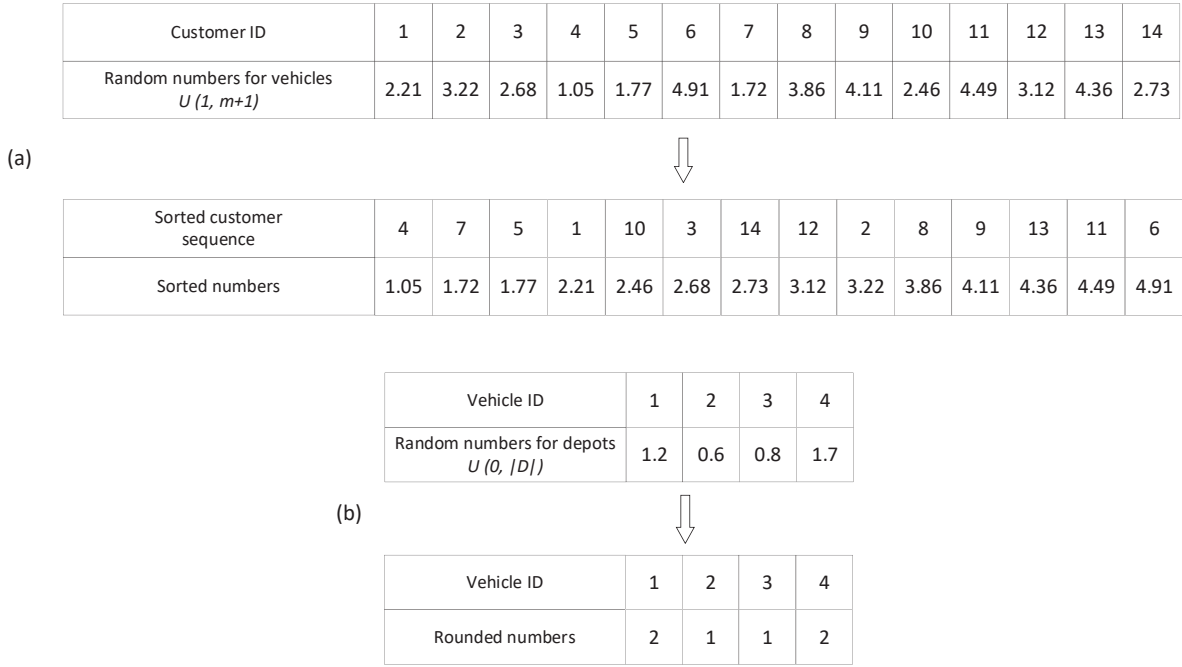


Fig. B.6. An example of random-key encoding scheme.

Appendix C. Data description

The range of parameters utilized in the data creation for random instances and the size of test problems are described in Tables C1 and C2, respectively. Moreover, the cost parameters utilized in this work are given in Table C3, adapted from [Sadrani et al. \(2022\)](#).

Table C1

Range of generated parameters for random instances.

Parameter	Value	Parameter	Value
Depot number	$DU[2, 5]$	Vehicle passenger-carrying capacity	$DU[6, 17]$ (pax)
Customer node number	$DU[3, 120]$	Vehicle freight-carrying capacity	$DU[10, 100]$ (item)
Node passenger demand	$DU[10, 200]$ (pas/h)	Standard deviation of driving time	$U[0, 15]$ (min)
Node freight demand	$DU[10, 250]$ (item/h)	Time window duration	$U[1, 700]$ (min)
Arc length	$U[2, 15]$ (km)		
Customer locations within x and y coordinates	$U[0, 100]$		

U: Uniform distribution.

DU: Discrete uniform distribution

Table C2
The size of test problems.

Class	Instance ID	Instance size ($ D , C $)
Small	S1	(2,7)
	S2	(2,10)
	S3	(2,14)
	S4	(2,17)
	S5	(2,20)
	S6	(2,24)
	S7	(2,27)
	S8	(2,31)
	S9	(2,33)
	S10	(2,37)
Medium	M1	(2,41)
	M2	(2,45)
	M3	(2,50)
	M4	(2,56)
	M5	(2,60)
	M6	(2,66)
	M7	(2,71)
	M8	(2,78)
	M9	(2,85)
	M10	(3,24)
Large	L1	(3,37)
	L2	(3,43)
	L3	(3,50)
	L4	(3,55)
	L5	(3,61)
	L6	(3,72)
	L7	(3,86)
	L8	(4,82)
	L9	(4,94)
	L10	(4,110)

Table C3
Cost parameters.

Description	Unit	Value
Hourly human driving cost	€/veh-h	15.3
Passengers' trip time cost	€/h	6.2
Pollutant cost	€/g	0.09
Earliness penalty cost	€/h	2.4
Tardiness penalty cost	€/h	3.6
Vehicle operating cost	€/veh-h	7.8

Appendix D. Parameter calibration of algorithms using a Taguchi method

Proper calibration is a crucial step that can significantly impact the performance of metaheuristics (Goodarzian et al., 2021; Galarza Montenegro et al., 2021; Sahachaiseree et al., 2025; Sadrani et al., 2025). We do this by using a Taguchi experimental design technique, which is a well-used strategy in literature (e.g., Liu et al., 2020; Mokhtarzadeh et al., 2021; Tirkolaee et al., 2022). In essence, the Taguchi technique offers orthogonal arrays, making it possible to find the best combination of parameter levels with a reduced number of experiments, rather than evaluating all possible parameter combinations.

The Taguchi technique takes two types of factors into account: controllable and noise (uncontrollable) factors. For the robust design of experiments, this approach seeks to discover the ideal level of controllable factors while diminishing the effects of noise factors. To examine changes in the response variable, Taguchi developed a Signal-to-Noise (S/N) ratio [Eq. (D1)]:

$$\frac{S}{N} = -10 \times \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (D1)$$

where n represents the number of orthogonal arrays and y_i refers to the solution value in the i -th orthogonal array.

Table D1 lists the parameters (factors) of the metaheuristics and their corresponding levels. Our trials are carried out using Minitab 17 software under a three-level Taguchi strategy. For example, for an algorithm with 4 parameters (factors) at 3 levels, the Taguchi approach suggests a total of 9 trials (L9) for the parameter configurations (see Table D2). The results are shown in Fig. D.1, where the greatest mean of the S/N ratio determines the best level for each parameter (as reported in the final column of Table D.1).

Table D1

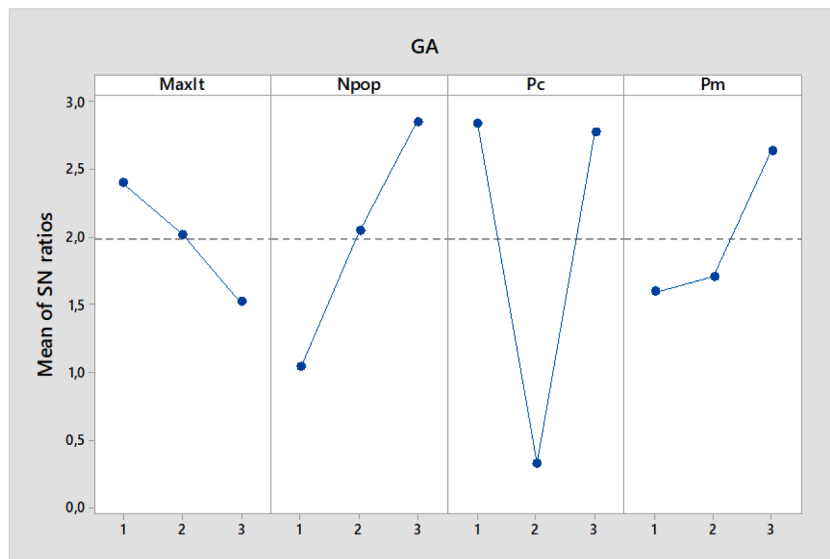
Algorithms' parameters and their corresponding levels.

Algorithm	Factors	Level	2	3	Best identified level
		1			
GA	<i>MaxIt</i>	150	200	250	1
	<i>N_{pop}</i>	55	65	75	3
	<i>Pc</i>	0.7	0.8	0.9	1
	<i>Pm</i>	0.1	0.2	0.3	3
PSO	<i>MaxIt</i>	150	200	250	1
	<i>Swam_Size</i>	55	65	75	2
	<i>c1</i>	2	2.1	2.2	1
	<i>c2</i>	2	2.1	2.2	3
GWO	<i>MaxIt</i>	150	200	250	1
	<i>N_{pop}</i>	40	60	80	2
PSA-GA	<i>MaxIt</i>	150	200	250	2
	<i>Nbor_{pop}</i>	5	10	15	2
	<i>Pc</i>	0.7	0.8	0.9	3
	<i>T₁</i>	10	15	20	1
	<i>α</i>	0.90	0.95	0.99	2

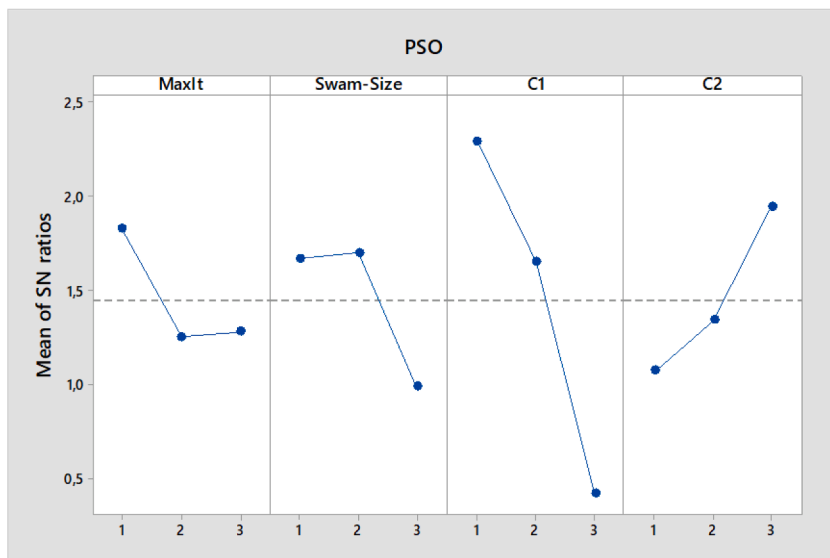
Table D2

Taguchi orthogonal array L9 (for 4 factors at 3 levels).

Trial number	Factor	B	C	D
	A			
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

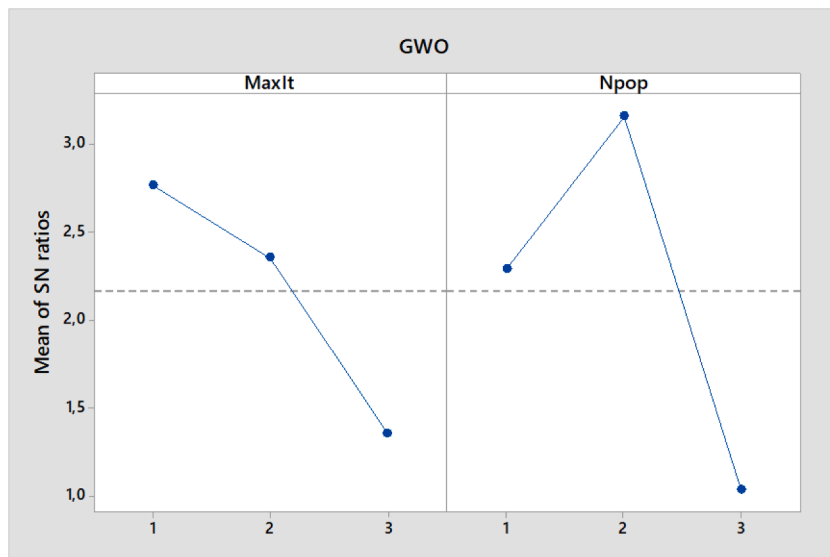


(a) GA

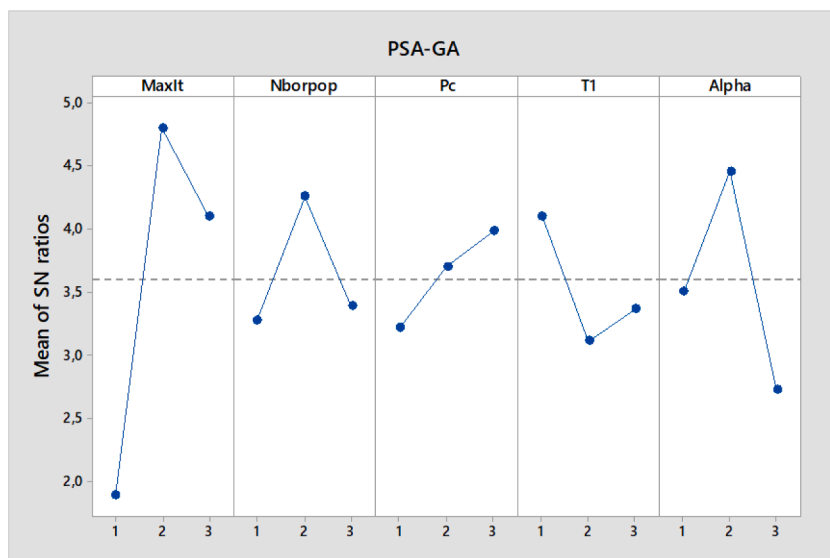


(b) PSO

Fig. D.1. Taguchi test results for tuning the algorithms' parameters.



(c) GWO



(d) PSA-GA

Fig. D.1. (continued).

Appendix E. Results of algorithms

Figs. E.1 and E.2 present the CPU times and solution gaps of the tested algorithms. E.2 (a) shows the solution gaps of the meta-heuristics relative to the optimal solutions obtained from Gurobi for small and medium-scale instances. Furthermore, the RPDs of the algorithms in large-scale examples are displayed in Fig. E.2 (b).

Overall, the PSA-GA delivers superior results compared to the other tested algorithms, with no or negligible gaps from Gurobi's optimal solutions. Similarly, the PSA-GA consistently outperforms the other algorithms in large-scale samples, where no alternative algorithm surpasses its performance, yielding RPDs of zero for the PSA-GA [see Fig. E.2 (b)]. In addition, the results show that GWO performs better than GA and PSO (see Figs. E.1 and E.2). The comparison between the GA and the PSO reveals that the GA generates superior solutions across most instances. Moreover, the GA outperforms the PSO regarding CPU times, as depicted in Fig. E.1, where the PSO exhibits longer CPU times in all samples.

In Fig. E.3, we also present the convergence profiles of the algorithms for various-sized examples (S5, M7, and L8). The PSA-GA consistently exhibits a faster convergence rate compared to the other algorithms across all examples.

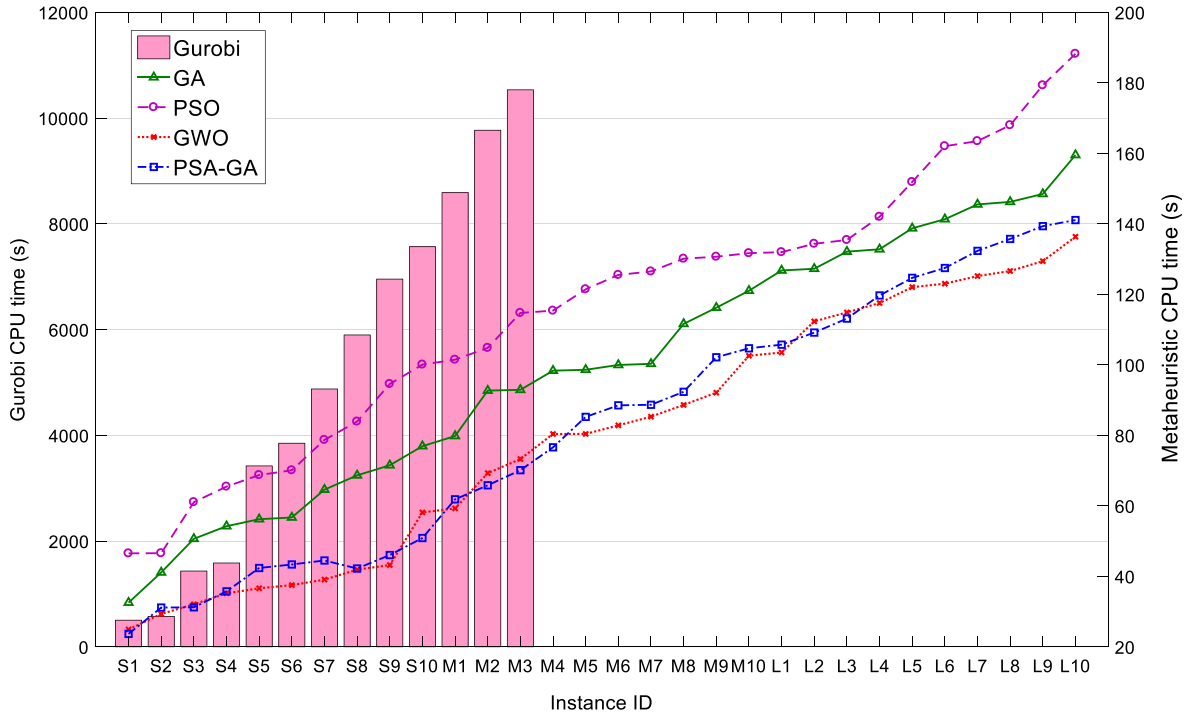
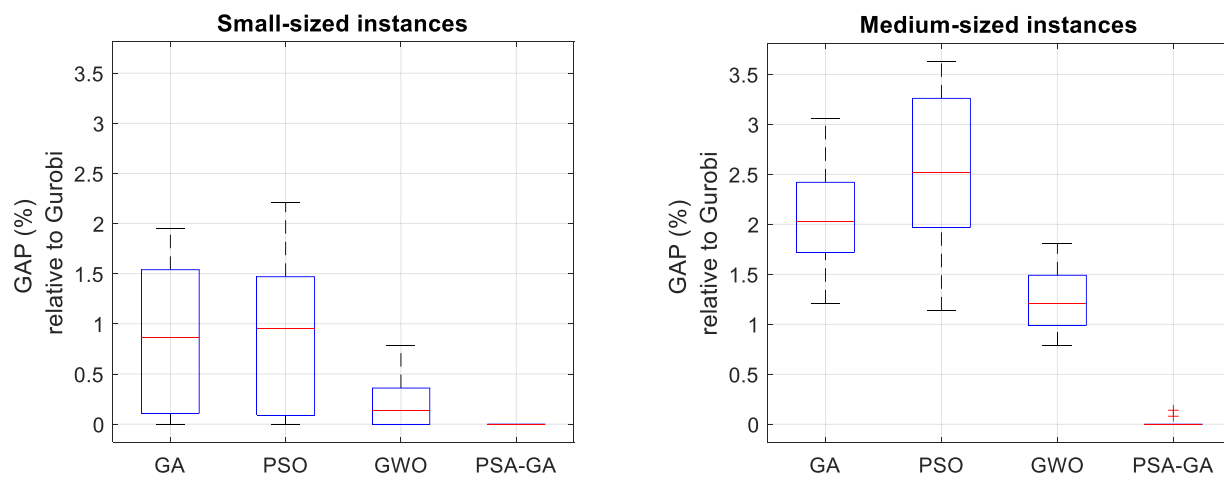
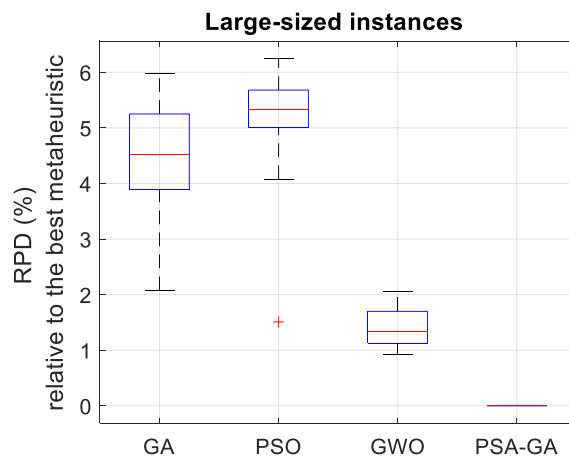


Fig. E.1. Comparison of algorithms based on CPU time.



(a) Comparing solution gaps in small and medium-sized instances:
Relative to the optimal solutions from the Gurobi solver.



(b) Comparing solution gaps in large-sized instances:
Relative to the best-found solution among all the metaheuristics.

Fig. E.2. Comparison of algorithms based on solution gaps.

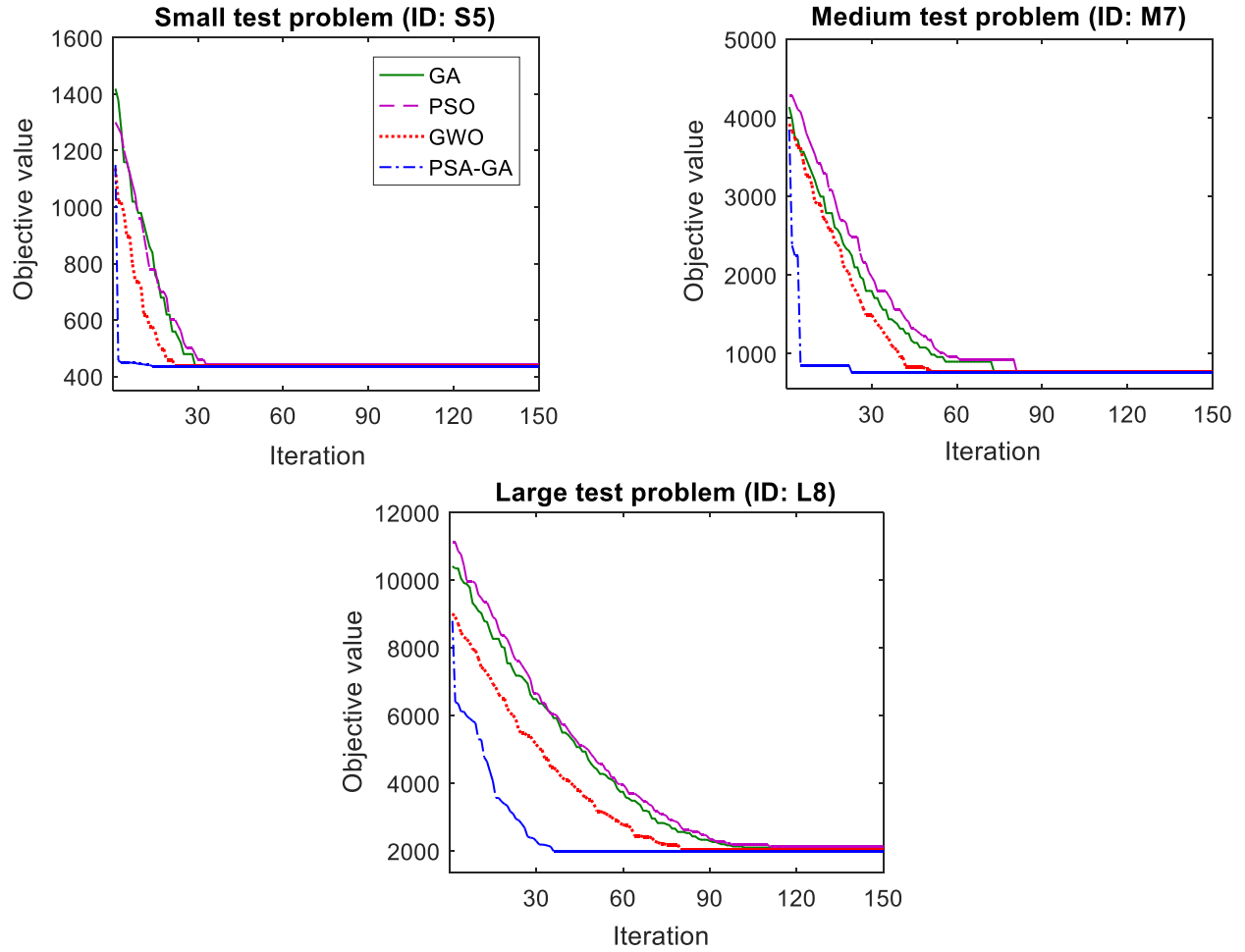


Fig. E.3. Convergence behavior of algorithms.

Appendix F. Wilcoxon signed rank test results

We employ the nonparametric Wilcoxon signed rank test (at a 0.05 significance level) to more thoroughly assess if there is a meaningful difference between the metaheuristics' findings regarding the solution quality metric. Table F1 shows the p -values obtained from pairwise analysis of the algorithms, indicating a statistically significant difference in their solution values ($p\text{-value} \leq 0.05$). Accordingly, the results of the Wilcoxon test confirm that the PSA-GA outperforms the other three algorithms (GA, PSO, and GWO). The results also highlight the GWO's superiority over both GA and PSO. Moreover, the GA performs better than the PSO in solving the proposed problem.

Table F1

The p -values of the Wilcoxon test.

Algorithms	p -values
PSA-GA vs. GA	0.000
PSA-GA vs. PSO	0.000
PSA-GA vs. GWO	0.000
GWO vs. GA	0.000
GWO vs. PSO	0.000
GA vs. PSO	0.044

Appendix G. Demand distribution in the case study

The demand representation in the case study is designed to capture both spatial and temporal variation in passenger and freight activity. Passenger demand is based on anonymized historical DRT records from the local transport operator in Kirchheim bei

München. Due to confidentiality agreements, the underlying raw OD records cannot be publicly disclosed. Therefore, we report aggregated demand summaries rather than raw OD data.

Freight demand is synthesized to represent parcel delivery activity in suburban Germany, using indicative parcel-delivery volumes and distribution trends reported in the KEP-Studie 2023. Since detailed parcel-level delivery data were not available for the case-study area, freight demand is allocated across customer nodes and time periods to reflect heterogeneous delivery requirements while keeping the total daily parcel demand consistent with the assumed suburban delivery context. Both passenger and freight demand vary across customer nodes and time periods; therefore, the base case does not assume a uniform demand distribution.

The eight-hour operating day is divided into four two-hour periods. Table G1 reports the temporal distribution of passenger and freight demand in the base case. Based on Table G1, the first and fourth periods (07:00-09:00 and 13:00-15:00) are treated as passenger peak periods, as they contain 61.9% of total passenger demand. Freight demand is relatively more concentrated in the middle periods (09:00-13:00), which together account for 56.5% of total freight demand, reflecting a more flexible delivery pattern compared with passenger demand.

To describe the spatial distribution (Table G2), customer nodes are grouped into high-, medium-, and low-demand categories based on their total daily request volume, calculated as the sum of passenger and freight requests assigned to each node. Nodes with more than 25 total requests per day are classified as high-demand nodes, nodes with 13-25 requests as medium-demand nodes, and nodes with 12 or fewer requests as low-demand nodes.

Table G1

Temporal distribution of passenger and freight demand in the base case.

Time period	Passenger demand	Share of passenger demand	Freight demand	Share of freight demand
07:00–09:00	188	32.0%	29	18.0%
09:00–11:00	106	18.0%	43	26.7%
11:00–13:00	118	20.1%	48	29.8%
13:00–15:00	176	29.9%	41	25.5%
Total	588	100%	161	100%

Table G2

Spatial distribution of passenger and freight demand in the base case.

Node group	Number of customer nodes	Passenger demand	Share of passenger demand	Freight demand	Share of freight demand
High-demand nodes	10	282	48.0%	70	43.5%
Medium-demand nodes	14	206	35.0%	61	37.9%
Low-demand nodes	14	100	17.0%	30	18.6%
Total	38	588	100%	161	100%

To provide a more detailed view of the relationship between passenger and freight demand across the network, Table G3 reports the demand at each individual customer node. At the individual-node level, passenger and freight demand show a moderate positive association, with a Spearman rank correlation of about 0.40 across the 38 customer nodes. Moreover, only 4 of the 10 nodes with the highest passenger demand are also among the 10 nodes with the highest freight demand. Therefore, the base case does not exhibit complete spatial overlap between passenger and freight demand. Nevertheless, the degree of spatial compatibility in the base case may partly contribute to the relatively high freight load utilization observed for IPFT. Greater spatial compatibility can facilitate joint routing, whereas weaker spatial alignment could reduce such opportunities and lower freight utilization and the efficiency benefits of integration.

Table G3

Passenger and freight demand at individual customer nodes.

Node	Group	Passenger	Freight	Combined
1	Low	10	2	12
2	Low	6	1	7
3	Low	9	0	9
4	Medium	11	2	13
5	High	31	6	37
6	High	34	4	38
7	Medium	14	6	20
8	High	27	3	30
9	Low	6	0	6
10	Medium	13	3	16
11	Medium	14	10	24
12	Low	8	2	10
13	Low	9	1	10
14	Low	4	2	6

(continued on next page)

Table G3 (continued)

Node	Group	Passenger	Freight	Combined
15	Low	7	2	9
16	Low	10	2	12
17	Medium	13	7	20
18	Low	0	11	11
19	Medium	20	5	25
20	Medium	9	5	14
21	Medium	15	2	17
22	Low	8	2	10
23	High	34	8	42
24	Medium	22	1	23
25	High	19	16	35
26	Medium	12	7	19
27	Medium	19	3	22
28	High	37	8	45
29	High	27	0	27
30	High	22	18	40
31	Medium	12	6	18
32	Medium	13	2	15
33	Low	7	4	11
34	Low	8	0	8
35	High	22	4	26
36	Medium	19	2	21
37	Low	8	1	9
38	High	29	3	32
Total		588	161	749

Appendix H. Monte Carlo simulation technique

Here, we outline the Monte Carlo simulation (MCS) technique for handling uncertainty in solving the problem, specifically related to driving times. By incorporating an MCS-based evaluation phase into our metaheuristics, we assess the objective function value (OFV) over multiple simulation runs instead of a single evaluation (Juan et al., 2023). The MCS serves as a subroutine within the metaheuristics, activating only during solution evaluation when OFV estimation is required (see Fig. H.1).

Step (1): Set the parameters of MCS: Define the simulation counter g and initialize its value as 1; let us define $\overline{OFV}^{(g)}$ as the estimated objective function value (OFV) in Eq. (1); and set the maximum number of simulations as G_{max} .

Step (2): Do sampling for driving times: The driving time of vehicles at each arc is a random variable whose mean and standard deviation are given. For each vehicle, the actual driving time between nodes i and j (c_{ij}) is sampled using a log-normal distribution function, i.e., $c_{ij} \sim \text{Lognormal}(o_{ij}, \sigma_{ij})$, where o_{ij} and σ_{ij} illustrate the mean and standard deviation of driving time between nodes i and j , respectively.

Step (3): Update the variables: Based on the sampled driving time value, update other variables in the model.

Step (4): Estimate the OFV: Compute and update the $OFV^{(g)}$ based on Eq. (1), and the final output of the OFV is achieved by averaging the simulated samples:

$$\overline{OFV}^{(g)} = \frac{OFV^{(g)} + (g - 1) \cdot \overline{OFV}^{(g-1)}}{g}$$

Step (5): Control the stopping criterion: Add the number of simulations by 1, $g = g + 1$. If $g < G_{max}$, return to Step (2); otherwise, terminate and return the estimated OFV, $\overline{OFV} = \overline{OFV}^{(g)}$.

Fig. H.1. Steps of the Monte Carlo simulation technique.

Data availability

The authors do not have permission to share data.

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